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Exploring Mobile Map App Usage: A Geospatial Study of Touchscreen Interactions and Contextual Influences

GEO 511 Master's Thesis

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Abstract

Mobile map applications serve as versatile tools for modern navigation and location-based searches, aiding activities ranging from exploring unfamiliar areas, planning routes from home, to purchasing public transport tickets while traveling. Despite their widespread use across various contexts, there remains a significant gap in our understanding of how these diverse situations influence user interactions with smartphones. This work aimed to discern the behavioral patterns of mobile map app usage, with a particular focus on how these patterns vary based on user mobility (stationary vs. non-stationary) and various contextual factors such as home and work locations, points of interest (POIs) and transportation modes. Employing tappigraphy, an ecological momentary assessment that captures taps with high temporal resolution and ecological validity (Reichenbacher and Bartling, 2023; Zingaro et al., 2023; Zingaro and Reichenbacher, 2022), this thesis examined touchscreen interactions in conjunction with GPS data to investigate the use of mobile map apps in real-world environments. A geospatial analysis was performed on the data from 39 participants with use of the Trackintel library (Martin et al., 2023). The findings suggest that map app usage is influenced by the user's mobility state, with distinct apps being preferred depending on the use context. The study concludes that enriching tap data with location-based context improves understanding of mobile app behavior, thereby providing valuable insights for app developers to improve usability and user experience.

Keywords: *Map App Usage, Tappigraphy, Mobile Applications, Smartphone, Use Context, Mobility*

Zusammenfassung

Mobile Kartenanwendungen stellen vielseitige Werkzeuge für die moderne Navigation und standortbezogene Suche dar. Ihr Einsatzbereich erstreckt sich von der Erkundung neuer Regionen und der Planung von Routen von einem bestimmten Ausgangspunkt bis hin zum Erwerb von Fahrkarten für öffentliche Verkehrsmittel wenn Unterwegs. Obgleich ihre Nutzung in diversen Kontexten weitverbreitet ist, besteht nach wie vor eine signifikante Forschungslücke in Bezug auf das Verständnis darüber, wie die unterschiedlichen Situationen die Interaktionen der Nutzer mit Smartphones beeinflussen. Ziel dieser Arbeit war es, die Verhaltensmuster bei der Nutzung mobiler Karten-Apps zu untersuchen, mit besonderem Augenmerk darauf, wie diese Muster je nach Mobilität des Nutzers (stationär vs. nicht-stationär) und verschiedenen Kontextfaktoren wie Wohn- und Arbeitsort, Points of Interest (POIs) und Verkehrsmittel variieren. In der vorliegenden Arbeit wurden Touchscreen-Interaktionen in Verbindung mit GPS-Daten untersucht, um die Nutzung von mobilen Karten-Apps in realen Umgebungen zu analysieren. Dabei wurden die Methode der Tappigraphie (ein "Ecological Momentary Assesment", EMA) eingesetzt, welche Touchscreen-Aktionen mit hoher zeitlicher Auflösung und ökologischer Validität erfasst (Reichenbacher and Bartling, 2023; Zingaro et al., 2023; Zingaro and Reichenbacher, 2022). Unter Verwendung der Trackintel-Bibliothek (Martin et al., 2023) wurde eine Geodatenanalyse anhand von 39 Teilnehmern durchgeführt. Die Ergebnisse deuten darauf hin, dass die Verwendung von Karten-Apps durch den Mobilitätszustand des Nutzers beeinflusst wird, wobei in Abhängigkeit vom Nutzungskontext unterschiedliche Apps bevorzugt werden. Die Studie kommt zu dem Schluss, dass die Ergänzung von Tap-Daten mit standortbasiertem Kontext das Verständnis für das Verhalten mobiler Apps verbessert und damit wertvolle Erkenntnisse für App-Entwickler generiert, die zu einer Optimierung der Usability und des User-Experience beitragen.

List of Acronyms

AA	Ambulatory Assessment
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
EMA	Ecological Momentary Assessment
GIScience	Geographic Information Science
GPS	Global Positioning System
LBS	Location-based services
MoT	MapOnTap
OSM	OpenStreetMap
OSNA	Online Social Network Activity
POI	Point of Interest
TI	Trackintel
UZH	University of Zurich

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1 Introduction

1.1 Motivation

Today's world is characterized by the ubiquitous use of smartphones —anytime, anywhere. The number of smartphone subscriptions has steadily increased since 2016 and is expected to continue to grow (Statista, 2024). People increasingly rely on mobile map applications and location-based services (LBS) as tools for modern navigation and search for places, which generate large amounts of geospatial and behavior data. As a result, the valuation of the digital map market has also increased rapidly since 2018 and is projected to grow to USD 73.1 billion in 2033 (Saha, 2023). For example, according to a recent report, Google Maps alone has an average of 1.8 billion monthly users worldwide (Wylie, 2024), reflecting the growing demand for accurate real-time geospatial services.

The considerable expansion in demand and market growth of smartphones and map applications can be attributed to the versatility of smartphones, which enable users to access a wide array of services, at any time and anywhere. This also means that mobile (map) apps are used in different contexts for numerous purposes. For instance, mobile map apps can be used in wayfinding, helping us navigate when planning a route or searching for desired destinations (Brügger et al., 2019; Montello and Freundschuh, 2005). Moreover, map apps can also serve to improve spatial knowledge of the environment. Recently, Schade et al. (2023) designed and evaluated a mobile map app to enhance the exploration of the user's surroundings through gamification, creating an interactive way to improve spatial cognition.

Map use contexts are highly diverse, ranging from pedestrian navigation in unfamiliar urban environments, route planning at home, to in-vehicle route planning for long-distance travel, where each context imposes unique constraints and requirements on the design and functionality of maps (Bartling et al., 2022, 2023). Furthermore, the small screen sizes and touch-based interactions characteristic of mobile devices may present usability challenges. Ultimately, a nuanced understanding of mobile map usage patterns and the circumstances under which people engage with these map apps is crucial to effectively design or enhance mobile map apps that not only meet functional requirements but also provide a seamless and satisfying user experience (Griffin et al., 2017). This may involve adapting map content, symbology, and interaction methods to enhance readability, reduce cognitive load, and improve overall usability on mobile platforms.

Despite the widespread adoption of mobile map app services, a significant gap remains in understanding their everyday usage patterns. Research utilizing highly ecologically valid or publicly available data to study phone usage with consideration of use context is scarce (Khan et al., 2020; Kim et al., 2019). Specifically, there is a notable lack of theoretical understanding of the relationship between use context and user behavior Kim et al. (2019), as well as the link between app usage and mobility choices Khan et al. (2020). This research deficit may be attributed to concerns about potential data misuse, particularly Global Positioning System (GPS) information, and the delicate balance between privacy and accuracy in long-term phone use data collection (Power et al., 2021). It is therefore imperative to study phone use in conjunction with contextual factors, such as location preferences, app interests, and habits, in order to bridge the research deficit and gain insight into users' needs. This understanding can subsequently inform improvements in mobile app design (Bartling et al., 2022).

To address privacy concerns while maintaining high ecological validity, a novel approach is required. This thesis proposes the use of tappigraphy, a method recently introduced to the field of Geographic Information Science (GIScience) (Reichenbacher et al., 2022; Zingaro et al., 2023; Zingaro and Reichenbacher, 2022), to collect data on the usage of everyday mobile maps and improve the analysis by extracting context from GPS data. Tappigraphy involves collecting and analyzing touchscreen events on smartphones (Balerna and Ghosh, 2018) (see section 2.1). The aim is to leverage the high temporal scale of taps and GPS data to investigate low-level human-app interactions in map apps.

This approach offers several advantages over existing methodologies. It provides more granular information compared to studies that rely solely on the volume of traffic from the mobile network, allowing deeper insights into user behavior (De Nadai et al., 2019; Shafiq et al., 2012; Trestian et al., 2009; Yang et al., 2016). Moreover, it expands upon previous tappigraphy map use research by incorporating location information (Reichenbacher et al., 2022), and extends existing methodologies that consider the retrieval of home location and the computation of distance away from home by integrating location-based context with GPS data (Zingaro et al., 2023; Zingaro and Reichenbacher, 2022).

1.2 Research Questions

The primary objective of this research is to use data from the MapOnTap (MoT) study to gain a deeper understanding of the behavioral patterns associated with using of mobile map apps in the context of human mobility.

To this end, we characterize human mobility as either stationary or non-stationary. The term *stationary* describes the act of remaining in a geographical space for a designated period of time (Martin et al., 2023; Teixeira et al., 2021). Conversely, we define *non-stationary* as the logical complement of stationary behavior; describing individuals who are in motion or transit (Smolak et al., 2022). To enhance the understanding of mobility with contextual information, differentiation can be made between modes of transport for non-stationary movement (i.e., fast or slow mobility), and a purpose (home vs. work) or Point of Interest (POI) classification for stationary locations. In accordance with the terms of the trackintel (TI) library for human mobility data (Martin et al., 2023), the spatial entities for stationary data are called staypoints, and for non-stationary data triplegs (see subsection 3.2.3).

Following the objective, the research questions of this master thesis are:

1. What tapping and usage patterns can be identified in mobile map apps at a macro-level depending on their state of mobility, i.e., stationary or non-stationary?

2. Can different map usage behavior be derived based on context enrichment of stationary locations (purpose and POI) and mode of transport (fast vs. slow mobility)?

3. How do tapping and usage patterns in map apps differ at a micro-level depending on their state of mobility and context-enriched state of mobility?

2 Related Work

This chapter examines the existing literature relevant to this thesis. The review begins with definitions of the key terminology essential to the methodological approach in the context of empirical research using smartphones. Subsequently, the focus shifts to related work, examining studies on mobile phone usage that consider contextual factors. This is followed by an exploration of research linking app usage with mobility patterns. The chapter concludes with a specific focus on studies investigating map app usage, which forms a critical component of this thesis. By synthesizing the key concepts and findings from previous research, we establish the foundation for investigating the interaction between mobile map app usage and context.

2.1 Terminology

Understanding the key terms that frame this study is essential for interpreting the results and methodologies used in mobile app usage research. In behavioral science, *ecological validity* describes the ability to derive research findings in real-world, naturalistic circumstances (Andrade, 2018; Lewkowicz, 2001). This concept aligns with *Ambulatory Assessments* (AA), which refers to the use of computerized or digitized methods to study daily life through self-reports, behavioral observations, psychological test data, movement behavior, or physiological measurements(Fahrenberg, 2021). Similarly, an *Ecological Momentary Assessment* (EMA) is defined as the real-time, repeated sampling of user behavior and experience in a natural environment (Shiffman et al., 2008). These approaches are increasingly applied to mobile phone usage studies, where smartphones serve as tools for unobtrusive, in-situ data collection.

Smartphones

With the rise of smartphones, AA methods have evolved, allowing researchers to study participants' phone use remotely. These methods offer advantages over traditional studies by facilitating data collection over extended periods (weeks or months)

(De Nadai et al., 2019; Falaki et al., 2010; Huber and Ghosh, 2021) or with larger study sizes (e.g., (Böhmer et al., 2011; De Nadai et al., 2019; Verkasalo, 2009; Yang et al., 2016)). Furthermore, smartphones are also equipped with numerous built-in sensors (e.g., GPS, accelerometer, light sensor, gyroscope, etc.) that can provide additional insights into user activities and contexts beyond app usage (Otebolaku and Andrade, 2016; Straczkiewicz et al., 2021; Huang and Onnela, 2020).

Tappigraphy

The introduction of tappigraphy, an EMA method that collects and analyzes smartphone touchscreen events, offers a novel approach to studying mobile app use (Balerna and Ghosh, 2018). This technique offers the potential to gain insight into human app use behavior during everyday activities through the continuous logging of taps on smartphones at a millisecond timescale, thereby providing high-resolution data with high ecological validity (Reichenbacher and Bartling, 2023; Zingaro et al., 2023; Zingaro and Reichenbacher, 2022). A key strength of the method is its unobtrusive and remote data collection approach, which captures in-situ ambulatory human-system interface interactions (Reichenbacher et al., 2022). Furthermore, due to the high temporal scale of data collection, collecting private information on the user or usage is unnecessary, such as demographic information or audiovisual material (Zingaro et al., 2023). Therefore, tappigraphy balances the competing interests of privacy rights and data access (Power et al., 2021), rendering it particularly suitable for exploring human behavior in everyday activities (Reichenbacher et al., 2022).

Originally developed and implemented in the field of behavioral and cognitive neuroscience, tappigraphy was used to study and identify behavioral patterns, including cognitive performance, sleep patterns, and sensorimotor activity, in individuals with epilepsy (Balerna and Ghosh, 2018; Duckrow et al., 2021; Huber and Ghosh, 2021). Recently, it has been introduced to the fields of GIScience and LBS (Reichenbacher et al., 2022; Zingaro et al., 2023; Zingaro and Reichenbacher, 2022). Compared to conventional user tracking methods in cartography or GIScience, tappigraphy is an unobtrusive and remote approach. Researchers refrain from contacting or interfering with participants' activities, a feature lacking in traditional techniques such as self-report questionnaires (Fennell et al., 2019; Khan et al., 2020) or interviews/debriefings (Riegelsberger and Nakhimovsky, 2008). This reduces costs, which enables an increase in the length of the study duration (i.e., weeks, months, etc.) and/or the sample size (Reichenbacher et al., 2022).

However, tappigraphy is limited to capturing app usage involving haptic interactions (Reichenbacher et al., 2022), which is a consideration given that some participants extensively interact with map apps while others do not (Brügger et al., 2019). This limitation leads into the broader discussion of current research on app usage, particularly in the context of mobile maps and location information.

Understanding these foundational terms is essential as we examine how different contexts influence mobile phone usage. The next section will explore how the use context of mobile phone can shape app usage patterns and the overall user experience.

2.2 Use Context in Mobile Phone Usage

The activity theory, formulated by Russian psychologists in the early 20$^{\text{th}}$ century, serves as a framework for modeling human activities (Kaptelinin et al., 1995). It offers a valuable lens for understanding mobile phone usage by framing activities as the interaction between the subject, the object, and tools (Kaenampornpan and O'Neill, 2004; Kim et al., 2019).

Contextual factors also play a critical role in describing an individual's activity (Kaenampornpan and O'Neill, 2004). Context is a multifaceted concept with various interpretations in different fields. In this discussion, we will concentrate on its definition in the field of human-computer interaction. According to Abowd et al. (1999, p. 304), context refers to "any information that can be used to characterize the situation of an entity [person, place or object]" relevant to the human-system interaction. When this definition is applied to users, this is called the use context (Kim et al., 2019), which encompasses situational factors such as location, time, user characteristics, and technology (Kaenampornpan and O'Neill, 2004; Kaasinen, 2003).

The notion of geographic relevance further enriches our understanding of context in use. Originating from Geographic Information Science, geographic relevance emphasizes a user's need for geographic information depending on their specific situation (Raper, 2007). This approach aims to facilitate user activities by delivering pertinent information that addresses essential questions of where, what, and when (Reichenbacher et al., 2009). Understanding these contextual elements is crucial because they directly influence how and when mobile services are used (Verkasalo, 2009). Moreover, the insight into these learned patterns of context can help predict and adapt to future user behavior (Otebolaku and Andrade, 2016).

Location information can be further enriched to provide more meaningful insights. This process involves transforming raw GPS data into higher-level contextual elements through context-aware methods (Abowd et al., 1999; Bartling et al., 2023).

Enriched location data allows for a deeper understanding of how map apps are used in specific scenarios, such as providing tailored suggestions based on the user's real-time context or transportation mode. Such enrichment is particularly important for LBS, which rely heavily on precise contextual information to deliver personalized user experiences (Kim et al., 2019).

According to activity theory, the focal activity in this thesis is the use of map apps, where the subject is a user that engages with a mobile device to achieve a specific goal. Various contextual factors further shape this activity. To systematically categorize these factors, Bartling et al. (2023) proposed a taxonomy that organizes the contextual components of mobile map usage into three primary categories. Extrinsic context involves the technological and environmental factors, intrinsic context refers to the user's individual and cognitive attributes, and behavioral context encompasses physical or digital user activities. The detailed framework for examining the interaction among the user, the object, the tool, and the contextual elements in the utilization of map apps is illustrated in *Figure 1* visualizes the activity theory and activity-centric view for the use of the mobile map apps.

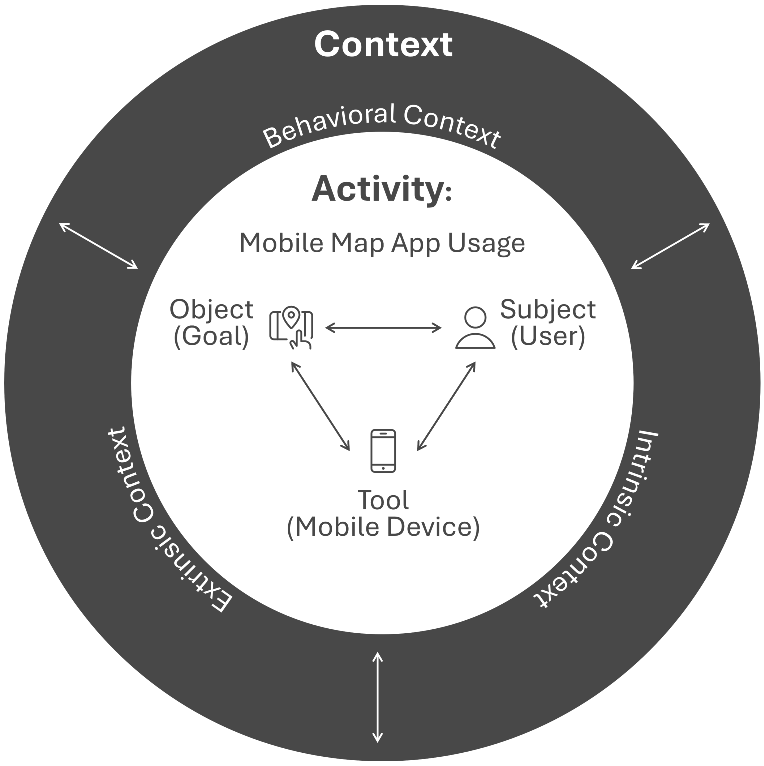


Figure 1: Activity Framework and Context for Map App Use (adapted from Kim et al. (2019), enhanced with Map Use Context from Bartling et al. (2023))

In light of the extensive range of contextual factors at hand, this literature review is concentrated on studies that incorporate location-based information. A number of studies have enriched the location data with categorical information about where phone usage occurs (environmental context). For example, Böhmer et al. (2011) used

AppSensor to track app usage across different geographical regions and functional types, such as airports. They also contextualized non-stationary data with speed, finding that at speeds greater than 25 km/h, people were less likely to use apps of the Travel category.

Similarly, Do et al. (2011), used smartphone data to explore long-term usage patterns about places and social contexts. The location information was captured using a multi-modal approach consisting of GPS data and Wi-Fi access points. The semantic meaning of the places was assigned by the participants themselves, who manually labeled eight automatically chosen places from a predefined list of 11 categories, including home, work, transport, and restaurant. The phone information was given by the start and end time of an app session, though due to technical difficulties with the end of session data, they only considered usage frequency and not duration.

Further research has examined app usage by contextualizing locations into categories such as downtown areas, suburban zones, and university campuses (Shafiq et al., 2012) or across functional zones such as transportation, educational institution, work, and entertainment Yang et al. (2016). However, these studies relied on cellular traffic volume to as their phone usage data.

Although these studies offer valuable insights, they lack the fine-grained detail that tap data from the tappigraphy method provides, which captures direct interactions within an app. The enrichment of environmental and behavioral information, especially in the context of map apps, remains crucial because these applications provide a wide array of services that are heavily dependent on contextual factors (Abowd et al., 1999; Bartling et al., 2023). Given the importance of context in shaping app usage, the following section will explore how mobility influences these patterns, focusing on the dynamic relationship between user movement and app behavior.

2.3 Mobility and App Usage

In line with the taxonomy of map use context, mobility is part of the behavioral context category (Bartling et al., 2023). The dynamic relationship between user movement and app behavior remains an area that needs to be explored, particularly regarding how phone-session-based data can inform our understanding of mobile app interactions Khan et al. (2020). This section summarizes studies on general app usage related to mobility, excluding those focused exclusively on map apps (see 2.4). It begins with research restricted to stationary app usage, followed by those incorporating non-stationary data.

In a study restricted to stationary app use, staypoints were defined as “small circular areas” where a participant stayed for at least 10 minutes Do et al. (2011, p. 355). For the place labeling, the staypoints were aggregated with a grid clustering algorithm, to clusters of a maximum distance of 250 m. Some findings included that home, work, friend-home were the most popular places. Moreover, maps were accessed the most in places of holiday, relaxation and restaurants.

Another study limited to stationary app use was a six-month analysis conducted by De Nadai et al. (2019) to determine whether the digital behavior of people also exhibited constraints similar to those observed in physical and social spaces (Alessandretti et al., 2018). The ‘stop events,’ or what we refer to as staypoints, were defined as places where individuals had spent at least 15 minutes within a 50 m distance. The staypoints were then aggregated with a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) with at least one stop event within 45 m into ‘stop locations’ to characterize a person’s mobility. Instead of contextualizing the visited places with semantic meaning, they categorized participants as ‘explorers’ and ‘keepers’ in both the physical and social space based on their rate of discovering new locations that are visited regularly or applications. Based on this, they showed that the app capacity can help predict the mobility behavior and vice versa.

An early large-scale study that examined the connection between users’ application interests and mobility properties in both stationary and non-stationary states was Trestian et al. (2009). They analyzed anonymized trace information and base-stations locations for 7 days. The area of the base-stations ranged from several 100 m^2 to several square miles and was on average 4 km^2. To study the role of locations, they differentiated between home and work places based on the time of day spent in a location. They were pioneers in discovering the correlation between movement patterns and the access of apps. For instance, stationary users tended to access different apps than those who moved more often and visited more locations. Moreover, certain app categories were used more frequently in specific locations.

An alternative approach to understanding the influence of context on mobile phone usage is to categorize location data according to movement type. In a self-report survey without GPS data, Fennell et al. (2019) examined the relationship between mobile phone usage, physical activity, and sedentary behavior. Sedentary behavior was classified into three categories: sitting, standing, and moving. The hypothesis that cell phone use occurs mainly when sitting, compared to standing or moving, and that it is positively associated with sedentary behavior (low, mid, high) but not with physical activity was confirmed. As the data was self-reported, the findings were contingent on the subjects’ ability to accurately estimate their phone usage.

Consequently, this method does not match the ecological validity of automatically collecting location data from AAs.

Another comprehensive study on the influence of people's mobility, geospatial patterns, and preferences on the use of mobile apps with a higher degree of ecological validity was conducted by Yang et al. (2016). They used IP flow traces from a cellular provider to gauge app usage and mobility, characterizing mobility by the number of cells visited and by the radius of gyration, a metric for the size of the activity space (González et al., 2008). The cells were enriched with meaning by manually classifying them according to their function. The study found that an increase in mobility level led to increased app usage, albeit the effect varied according to category type.

Similarly, Verkasalo (2009) distinguished between users in a state of motion and those who were stationary, whether they were at home or at work. Unlike the data collection methodology employed by Fennell et al. (2019), Verkasalo's study collected data continuously and in-situ. However, the geolocation data is cell-based, and the data collection is limited to hourly logging. If a user spent less than 10% of their time in a cell, it was classified as being on the move; otherwise, the usage time in a cell, along with the hourly and weekday distribution, was used to attempt to classify a cell as home or work. The low temporal (hourly) and spatial (cell-based) resolution resulted in the fact that the algorithm identifying the context of only 324 of the original 861 participants.

To gain a more accurate understanding of app usage in various mobility contexts, the studies reviewed above point to the need for higher accuracy in location tracking and consideration of both stationary and non-stationary behaviors. Numerous mobility studies relied on less precise location data than GPS data (Fennell et al., 2019; Trestian et al., 2009; Verkasalo, 2009; Yang et al., 2016). They focused on contextual-enrichment solely for stationary app usage neglecting app usage during movement (De Nadai et al., 2019; Do et al., 2011), or considered enriched stationary settings but lacked further context into non-stationary behavior (Verkasalo, 2009; Trestian et al., 2009). However, to truly capture the nuances of users interact with apps, both stationary and non-stationary situations must be considered. Furthermore, existing research tends to measure app usage only in terms of access frequency and/or session duration, without exploring the detailed behaviors within app sessions.

Map apps, with their inherent connection to spatial data and mobility, offer a distinct perspective through which these dynamics can be explored in more depth. Thus, the next section will delve into research specifically focused on map apps, examining how they capture user interactions.

2.4 Map App Usage

While the studies in the previous section provided insights into general app usage patterns and mobility, map apps—by design—play a particularly pivotal role in understanding human mobility. This section focuses on research that directly investigates map app usage, a field that remains underexplored compared to general app usage studies. Although some studies have analyzed map apps as part of broader app usage investigations (Böhmer et al., 2011; Carrascal and Church, 2015; Do et al., 2011; Falaki et al., 2010; Trestian et al., 2009; Yang et al., 2016), relatively few studies concentrate exclusively on map app usage (Kiefer et al., 2017; Riegelsberger and Nakhimovsky, 2008; Savino et al., 2021; Zingaro et al., 2023; Zingaro and Reichenbacher, 2022).

In a multi-method approach to study how people downloaded, installed and used Google Maps for Mobile, Riegelsberger and Nakhimovsky (2008) tracked 24 participants over a two-week period in four different cities. They identified the goals and challenges encountered by users. However, this study was restricted by its exclusive reliance on qualitative methods such as briefings, interviews, and in-situ recorded usage. To study the user experience of map use depending on different degrees of adaptations, researchers have also used eye-tracking data in an controlled experiment (Kiefer et al., 2017). However, such studies require a significant time input from researchers for the data collection and are difficult to scale to larger study sizes. In this regard, the use of AA and EMA methods to study map app use is very limited.

Recently, the tappigraphy method has been introduced into the field of GIScience to study the use of numerous map apps (Reichenbacher et al., 2022; Zingaro and Reichenbacher, 2022; Zingaro et al., 2023). In an exploratory study of the tappigraphy method, Reichenbacher et al. (2022) investigated how much, when, for how long, and how people use mobile maps, beyond Google Maps. This was a larger-scale study with 211 participants who shared their data for at least two consecutive weeks. Similar questions were analyzed in the Master thesis of Weber (2021) at the individual and group level, or how app use changes depending on the time of day or day of the week using the same dataset as Reichenbacher et al. (2022). Both Weber (2021) and Reichenbacher et al. (2022) based their analysis on tappigraphy data collected by Ghosh et al. where user's location information was not collected. Recently, map tap data collected with the tappigraphy method has been studied in conjunction with GPS data (Zingaro et al., 2023; Zingaro and Reichenbacher, 2022). However, they restricted spatial factors to the distance between participants and their computed home location (Zingaro et al., 2023; Zingaro and Reichenbacher, 2022).

The only study to our knowledge to also use logged app usage data to study map apps was focused on Google Maps. Using a wrapped app, four distinct interaction states were studied: Search, Place, Direction, and Map-View Savino et al. (2021). Although this study provides detailed insights into in-app usage, it is restricted to a single map application and does not offer broader perspectives on mobile mapping services or the specific context of app use.

Building on the limitations identified in previous mobility and (map) app usage studies, this research aims to fill key gaps such as the reliance on low-precision location data, the lack of insights into within-app behavior, and the insufficient contextualization of both stationary and non-stationary movements. We introduce the novel methods of tappigraphy and MapOnTap (MoT) that collects fine-grained tap data and integrate it with GPS information to subsequently generate location-based context. Specifically, the approach distinguishes between stationary and non-stationary mobility states and augments these states with place-based information and movement behavior during app usage. The following section outlines the method, from preprocessing, data alignment, mobility state classification, and context enrichment of mobility states.

3 Methods

This chapter outlines the methodological framework utilized in this thesis. It encompasses the stages from data collection via tappigraphy and MoT to the data processing required for alignment, subsequent classification of the aligned GPS data, and the extraction of contextual information. This meticulous process lays the groundwork for the extraction of tapping and usage patterns of map applications depending on the state of mobility, i.e., stationary and non-stationary. An overview of the steps is visualized in the flow chart in *Figure 2*.

From preprocessing tappigraphy and GPS data to the visualization of the aligned tap data, the computations took place in a Python 3 environment. To automate the steps, the scripting was done in separate python files stored as functions and called up in Jupyter Notebook files.

Throughout this study, map applications are defined as applications from the Google Play Store which belong to the categories *Maps and Navigation* or *Travel and Local*. App developers assign their application to a predefined list of app categories (Play Console Help, 2024). Maps and Navigation as well as Travel and Local categories specifically address map use and travel services. The former category is defined as containing "navigation tools, GPS, mapping, transit tools, [and] public transportation", while the latter is defined for "Trip booking tools, ride-sharing, taxis, city guides, local business information, trip management tools, [and] tour booking".

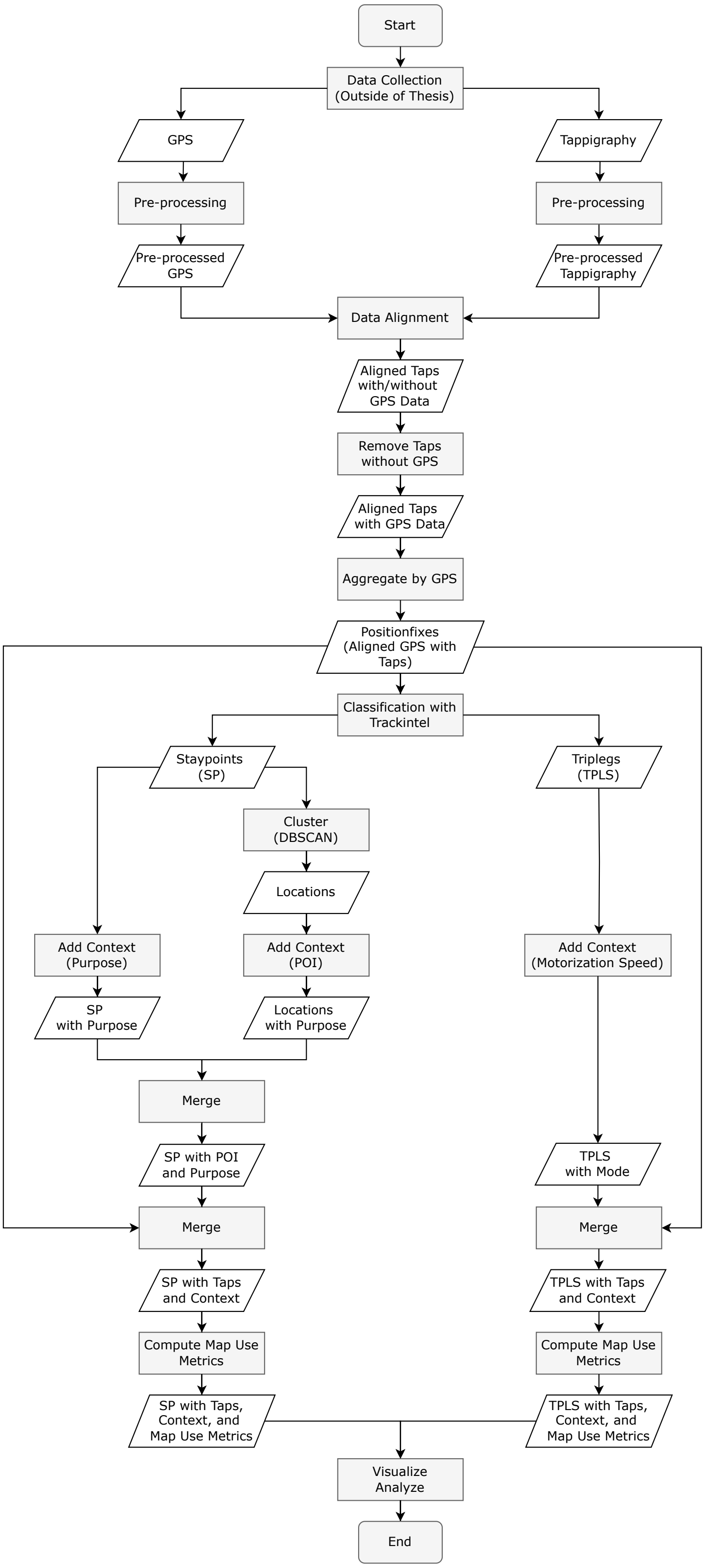


Figure 2: Flow Diagram of Methods

3.1 Data Collection

The initial phase of this research is based on data collected as part of the Map on Tap study conducted by PhD Candidate Donatella Zingaro at the Department of Geography of the University of Zurich (UZH) (MapOnTap, 2021). It is a project within the Digital Society Initiative and aims to understand how people use mobile map apps in their daily lives. The objective of the *MoT* project is to expand the existing knowledge on mobile app usage, which is a crucial prerequisite to conducting finer-grained studies of smartphone usage. To achieve this objective, *MapOnTap* app was developed at the Geographic Information Visualization & Analysis group at the UZH (Ceolini, 2023) and is based on the *TapCounter* app from QantActions, a spin-off company of the UZH, which explicitly excludes location data. The data obtained from tappigraphy alone is inadequate for the purpose of retrieving the spatial context of smartphone use, which is also of great importance for the understanding of how users employ mobile map apps. Consequently, the MoT app captures touch events on Android devices using the tappigraphy method and collects GPS data (MapOnTap, 2021).

The study collected taps from the moment the phone was unlocked until it was locked in a so-called phone session. It recorded the timestamp of the tap in addition to the name of the application and the Google Play Store category. The tappigraphy dataset consisted of user's tap data aggregated to app sessions, i.e., all consecutive taps in the same application. It includes information on the precise timing of each tap down to the millisecond, the start and end times of the app session, the number of taps in the app session, the name, and category of the app, and unique identifiers for the participant's phone session.

In addition to the tap data, participants were also asked to consent to the collection of their GPS data for the purposes of this study. They were given the option to enable or disable the GPS tracking functionality at any time during the study period. The GPS dataset included the location as longitude and latitude with the corresponding timestamp of the GPS information collected. Due to privacy concerns and the sensitive nature of GPS data, demographic information such as gender, age, or nationality was not collected.

3.2 Data Preprocessing

In order to analyze the usage of map applications in a geospatial context, a number of steps must be taken. The first step was the preparation of the data for the most complex and time-consuming step, the merging of the GPS and tap data. Following the alignment process, the trackintel (TI) library Martin et al. (2023) was used to categorize aligned GPS data into two states of mobility: stationary and non-stationary movement. The stationary category was further classified by purpose using the frequency or Online Social Network Activity (OSNA) method, or with POI data from OpenStreetMap (OSM). The non-stationary category was further classified through the calculation of tap speed to differentiate between slow and fast mobility.

It is important to note that phone sessions were derived directly from the raw tap data. In contrast, app sessions can be defined either by the taps that make up the phone sessions or, after data alignment, by their correspondence to the TI class.

3.2.1 Data Preparation

Given that the data was gathered through the MoT project, the initial phase of the thesis involved preprocessing the tap and GPS data to prepare it for the data alignment. For the GPS dataset, entries with missing data in the user ID, latitude, or longitude columns were removed. To mitigate issues in synchronizing GPS with tap data, duplicates and overlaps identified by GPS timestamps were removed. The original GPS data was stored as lists of GPS points. To make this data more accessible during the alignment, the GPS dataframe was exploded into an ordered dictionary of dictionaries where each entry corresponds to a positionfix, or 'raw' GPS points. The dictionary key consists of the GPS timestamps, while the values are the corresponding GPS information (timestamp, latitude, longitude, and altitude) as a dictionary.

Similar to the GPS data, the tap data was stored in lists of taps, referred to as "app sessions". They are defined as consecutive taps within the same app. App sessions corresponding to MoT ('ch.uzh.geo.mapontap') or SBB Preview ('ch.sb b.mobile.android.preview') were removed. Although MoT was a prerequisite for data collection, it is not a reliable indicator of typical usage patterns observed with map apps. On the other hand, SBB Preview is a test application of SBB Mobile ('com.google.android.apps.maps'). Moreover, to enhance clarity, the app name 'com.app.p2704IG' was renamed to 'com.app.stadtblatt.'

To make the relationship between app names and categories more accessible in the exploratory analysis, a dictionary was constructed for all app names containing the name-category relationship, and another for map apps only.

3.2.2 Tap and GPS Data Alignment

Following the preprocessing of GPS and tap data, the subsequent phase involved their temporal alignment. This process entailed the assignment of the temporal most proximate GPS data point, as stored in the ordered dictionary, to a tap timestamp that did not exceed the maximum interval threshold. In this context, multiple timeframes were tested, specifically 15, 30, 60, 120, 300, 450, 600, 900, and 1800 seconds, for three individuals. Ultimately, an alignment time of 900 seconds was selected by finding a balance between the lost data and how further TI classifications of the stationary data turned out.

Given that the ordered dictionary with GPS data lacked the user ID, the alignment and computation of the exploded GPS dictionary were carried out for a single user ID utilizing the function `process_per_participant`. To facilitate the alignment of data for multiple participants simultaneously, two functions were created: `align_gps_with_sessions` and `align_gps_with_sessions_and_export`. The former function compiled the aligned data of each user into a singular large dataframe, while the latter exported a CSV file of an individual's aligned dataframe post-computation. Both functions iterated through each user ID in the tap dataset, omitting users for whom no GPS data was available, and subsequently invoked `process_per_participant`. Exporting a CSV file for each individual proved beneficial in managing large datasets, minimizing the potential loss of progress during code execution interruptions.

The resulting aligned dataframe contained one row per tap with the columns: user ID, phone session ID, tap timestamp, app name, app category, latitude, longitude, and GPS timestamp. It is important to acknowledge that a GPS point could be associated with multiple taps. Moreover, a tap may not be aligned with a GPS point in the given time threshold. However, to apply functions from the TI library and to differentiate between stationary and non-stationary movements, GPS data was deemed essential. As a result, taps lacking GPS information were removed. Furthermore, the taps were grouped by user ID and GPS timestamp so that there were no duplicate GPS data for the geospatial analysis with TI. The relevant aligned tap information was stored in lists corresponding to each GPS point. We refer to this dataset as the aligned GPS data.

3.2.3 Trackintel Classification

This subsection provides an overview of the classification elements derived from aligning GPS data using the TI library. The TI library is structured around a hierarchical activity-based analysis framework in transport planning, which assumes that daily mobility involves performing activities in specific places and moving between locations for the next activity (Martin et al., 2023). While the TI hierarchy distinguished between various types of non-stationary movement (triplegs, trips, and tours), this analysis focuses exclusively on triplegs. Four key TI classes were employed in this study: positionfixes, staypoints, triplegs, and locations. An overview of these classes is visualized in *Figure 3*.

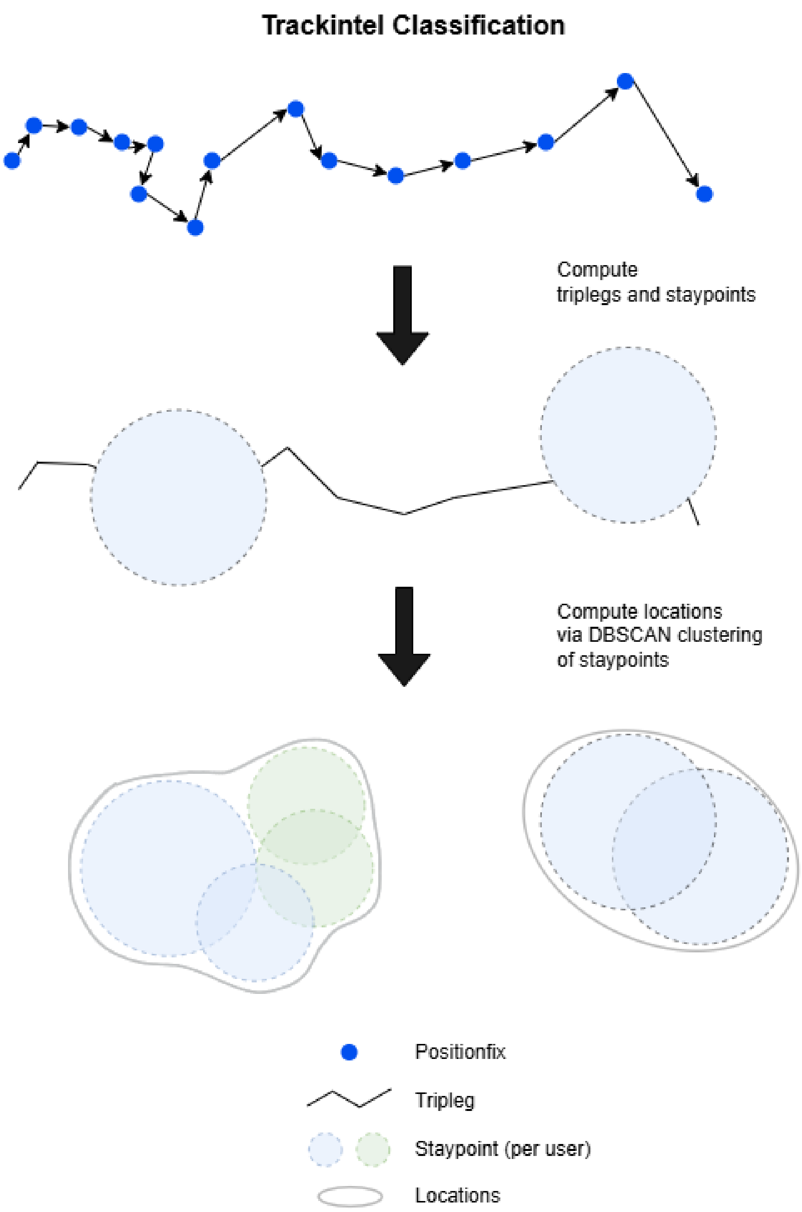


Figure 3: Trackintel Classfication: From Positionfixes to Staypoints, Triplegs, and Locations

The basic and smallest units are *positionfixes*, which are timestamped GPS points. The model's positionfixes input was given by the aligned GPS data. From the positionfixes, *staypoints* were generated, which correspond to the stationary mobility state classification. To complement the staypoints, they were clustered into what TI defined as *locations*. The combination of positionfixes and staypoints enabled the computation of triplegs, which is equivalent to non-stationary movement.

Extensive testing was conducted on the same three individuals utilized in the alignment computations to evaluate various time and gap thresholds for staypoints and triplegs. Specifically, a range of time thresholds (0.5, 1, 2, 5, and 15 minutes) was tested together with gap thresholds of 1, 5, 15, and 30 minutes to further refine the identification of stationary segments.

For triplegs, a series of gap thresholds (1, 2, 5, 10, 15, and 30 minutes) was examined along with the 5-minute time threshold and 15-minute gap thresholds for staypoints. This comprehensive approach allowed for a detailed analysis of how the movement segments varied in response to different gap thresholds. The results of these tests were also visualized to illustrate the changes in the movement segments, providing valuable information on the dynamics of the mobility patterns based on the selected thresholds. The different thresholds applied to compute the TI classes are summarized in *Table 1*.

Table 1: TI Thresholds for the Computation of Staypoints, Triplegs, and Locations

	Staypoint	**Tripleg**	**Location**
dist_threshold [m]	100	-	-
time_threshold [min]	5	-	-
gap_threshold [min]	15	15	-
method	-	between_staypoints	-
epsilon [m]	-	-	100
num_samples	-	-	1
distance_metric	-	-	haversine
agg_level	-	-	dataset

3.2.3.1 Staypoints and Locations

An individual remaining in a specific geographic location for a defined time period is considered to be stationary, and the place in question is referred to as a *staypoint* (Li et al., 2008; Martin et al., 2023). Unlike positionfixes, staypoints posses a semantic meaning, such as the purpose of the stay (Li et al., 2008; Martin et al., 2023). This differs from the TI *location* class, which consists of clustered staypoints. The TI staypoints class is established through the application of the sliding window detection algorithm initially proposed in Li et al. (2008) on the positionfixes, which incorporated both a minimum time threshold and a predefined distance. Additionally, the TI function provided the option to set a gap threshold to exclude of temporal gaps. This feature is particularly beneficial for datasets characterized by limited temporal tracking coverage (Martin et al., 2023).

Staypoints are characterized as shapely point features that include the timestamp of the first and last positionfix. By calculating the difference between the last and first positionfix timestamps, a new column labeled duration was created to facilitate comparisons regarding the length of time an individual spent while stationary.

The next step involved aggregating the nearest staypoints into *locations* using the DBSCAN algorithm implemented by Martin et al. (2023). Analyzing the significant places visited by an individual or a group is essential for conducting a more detailed examination of staypoints. Moreover, from a computational standpoint, extracting POIs from OSM for locations is more efficient than extracting them from staypoints due to the lower number of locations compared to staypoints. The use of clustered staypoints, or locations, offers insights into frequently visited places, which can then be analyzed across different contextual classes.

3.2.3.2 Triplegs

The counterparts to staypoints are triplegs, which are defined as segments of movement between the staypoints. For the computation of triplegs, the method *between_staypoints* was applied, with the consequence that positionfixes were uniquely assigned to a staypoint or tripleg, but not both. This is in contrast to the *overlap_staypoints* approach as outlined in Martin et al. (2023).

A tripleg is a shapely linestring element that contains the timestamp of the first and last positionfix assigned to the tripleg. The duration of each tripleg is computed in a manner analogous to that employed for staypoints.

3.3 Data Analysis

After computing the spatial entities, the next step involved labeling staypoints and triplegs with additional context. Since the tap data were not automatically inherited from positionfixes in the TI classifications, we merged them to create a stationary and non-stationary dataset with taps and context. To analyze map app usage, various metrics were calculated, including the tap speed and duration of the session. Finally, an overview of visualization methods and statistical analysis tests is presented.

3.3.1 Staypoint Context Labeling

Two methods were applied to generate environmental context about the staypoint: POI and purpose. Both approaches are described in this section.

3.3.1.1 OSM & Most Frequent POI

For the retrieval of POI information, this thesis employed the Overpass API (Raifer, nd) to retrieve POI tags from OSM. The function `get_tags_and_geom` was used to extract POIs and their geometries within a specified distance from a given point or within a defined polygon. The methodology was based on the OSMnx functions `features_from_point` and `features_from_polygon` which require a geometry column and a dictionary containing the tags for which POIs are to be extracted (Boeing, 2024). It was possible for zero, one, or multiple POIs to be retrieved for a single location. For the final dataset, we ended up using the tags computed from the center geometry of the locations, with a radius of 100 m. An overview of the selection of POI information and assignment to the staypoint is visualized in *Figure 4*.

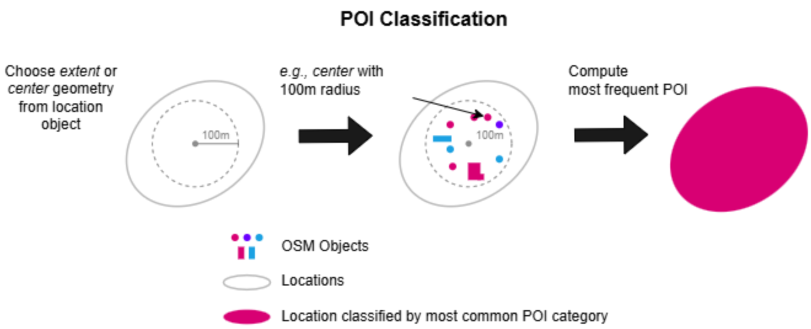


Figure 4: POI Classfication: Extraction, Computation and Assignment to Staypoints

Beyond retrieving all tags for a location and storing them in a list, the function `select_most_frequent_poi_tag` was applied to assign each location to a single tag, specifically the most common tag based on the POIs retrieved with `get_tags_and_geom` (see *Figure 3*). This facilitated comparisons between different staypoints and could be used in an exploratory analysis to provide an overview of the most frequently visited types of POIs. In a subsequent step, the specific POI tags were manually classified into broader categories, including food, education, transportation, entertainment, healthcare, residential, commercial, and tourism (Appendix A).

The analysis could specifically focus on transportation-related POIs to assess whether the usage of map applications was indeed higher in these locations, as found by (Yang et al., 2016). It was also reasonable to assume that individuals staying in hotels, hostels, or motels were tourists and thus more likely to utilize map applications.

3.3.1.2 Purpose: Home, Work

Another classification system for staypoints was based on what Martin et al. (2023) referred to as *purpose*, differentiating between home and work locations for every individual. Integrated within `location_identifier`, the TI library provided two methods for classifying staypoints by purpose: the frequency and the OSNA method Martin et al. (2023).

The frequency classification, based on the R package developed by Chen and Poorthuis (2021), assigned the label 'home' to the staypoint that was visited most often, and 'work' to the second most visited place. Staypoints that did not fall into either category were not labeled.

In comparison, the OSNA approach categorized the weekdays into three temporal segments: rest (2:00-8:00), work (8:00-19:00), and leisure (rest of the day) (Efstathiades et al., 2015; Martin et al., 2023). The staypoint with the greatest cumulative duration in the 'rest' and 'leisure' periods was designated to the 'home' label, whereas the 'work' period was assigned to the most predominant location in the work time frame. Originally devised by Efstathiades et al. (2015), the length of stay was computed from geo-tagged tweets. Martin et al. (2023) adapted the algorithm to use the duration of a staypoint.

3.3.2 Tripleg Context Labeling

After computing triplegs, the next step involved adding contextual information to these segments. As specific modes of transportation such as walking, jogging, cycling, and driving were not directly available from the GPS data, motorization speeds were utilized as a proxy. The TI function `predict_transport_mode` was applied to compute the average speed of the triplegs and categorize them into either *slow mobility* or *fast mobility*. The maximum speed for slow mobility was established at

<20 km/h. It encompasses modes of non-motorized transportation, including walking, jogging, scooting, and cycling. This threshold was derived from the average cycling speed of 17.92 km/h reported in the meta-analysis by Kassim et al. (2020). Segments with an average speed greater than 20 km/h were classified as *fast mobility*, which included travel by automobiles and public transportation modes such as trams, buses, and trains.

Our understanding of the tripleg differs from the interpretation presented by Martin et al. (2023), which posited that a tripleg corresponds to a single mode of transport. Given the heuristic nature of categorizing modes of transport into fast and slow mobility, this thesis refrained from adhering strictly to that definition.

3.3.3 Joining TI Classes and Computing Map Use Metrics

The tap information was exclusively stored in the positionfixes and not automatically inherited during the creation of the TI classes. Consequently, it was a prerequisite to join positionfixes with staypoints and triplegs to enable further analysis of tap use metrics related to the state of mobility. Before performing these joins, it was essential to prepare the positionfixes data, due to the one-to-many relationship between staypoints and positionfixes, as well as between triplegs and positionfixes. The function `aggregate_aligned_pfs` was utilized to group positionfixes by their associated staypoints or triplegs, concatenating the relevant tap information, including timestamps, app names, app categories, and phone session identifiers, into lists.

Subsequently, the TI classes were joined. In the case of staypoints, two joins were required: the first, between staypoints and locations (`join_sp_locs`), to incorporate location-based POI data, and the second, between staypoints and positionfixes (`join_sp_pfs`), to add the tap data from positionfixes. For triplegs, only a single join with positionfixes (`join_tpls_pfs`) was necessary, as the context labeling was performed within the tripleg data itself.

In the merged dataframes, the tap data for each staypoint or tripleg was stored in lists. From these datasets, the app usage metrics were computed with the `preprocess_grouped_taps`. For each entry in the input dataframe, representing an individual staypoint or tripleg, the function counted the unique number of app names and app categories accessed, determined whether a map app was used (True or False), and calculated the total number of taps per app name, app category, and map app, storing these values in dictionaries.

To normalize the tap counts, two main map use metrics, tap speed and duration, were calculated at a session level for staypoints and triplegs individually. A session refers to consecutive taps, either in the same app or app category. Sessions with fewer than two taps were excluded from the analysis, as it was not possible to compute the duration or the tap speed for these sessions. Unlike the original tap data, where app sessions were nested within phone sessions, app sessions in this analysis were computed relative to the staypoint or tripleg. We refer to this data as session metrics.

In instances where an app or category was accessed in multiple sessions within a staypoint or tripleg, the median value was computed. To account for the right-skewed distribution of the data and to facilitate comparisons across different apps or categories, a logarithmic transformation was applied to the median session duration (in seconds) and the median tap speed (taps per second). Consequently, references to session duration or tap speed will be the median of the logarithm of the median app session value of a staypoint or tripleg, respectively. These metrics were stored as dictionaries, with the app name or category as the key and the corresponding calculated statistic as the value.

As the focus of this study was specifically on map applications, the session metrics were specifically stored for map apps. However, the `preprocess_grouped_taps` method was also designed to compute session metrics for all app names and categories. In summary, we investigated "map app usage and mobility" across several dimensions. These included the number of taps within map apps during a staypoint or tripleg, the specific map applications accessed, and the session metrics associated with these apps and their respective categories.

3.3.4 Visualization and Analysis

After the calculation and storage of the tap data along with the map usage data for staypoints and triplegs, various forms of visualization were generated. To explore the geographical nature of the TI classes, the function `visualize_gdf` created an interactive map using Folium (python-visualization, 2024). By default, it will color the data by user ID, but it is possible to color by whether a map app is present in a TI class (except for locations). One can click on a single element to check information like the user ID, for staypoints and triplegs the duration, and if the element includes map app usage, the pop-up also includes the map app session metrics.

The function `create_barplots` provides a means to visualize categorical data in a barplot from a dataframe or a series. Numerical data in a dataframe were visualized as boxplots with the `create_boxplots` function. For data stored in dictionaries, the functions `create_barplot_df_dict` and `create_boxplot_df_dict` create plots by extracting the keys and values stored within the dictionaries. Finally, with `create_grouped_boxplot` one can visualize the distribution of a column grouped by the different values, which was useful for the map app session metrics grouped by the context categories.

With the `create_marimekko` function, categorical data can be plotted across two variables. This is used to visualize the staypoint and triplegs labels on the x-axis, and the proportion of map app usage on the y-axis. It is based on the `mosaic` function from the statsmodels.graphics.mosaicplot module (Perktold et al., 2023).

To take a closer look at which map apps had the highest tap counts in staypoints, triplegs, or a certain staypoint or tripleg label, we created Sankey diagrams with the `create_sankey` function. This function makes use of the plotly.graph_objects module (Plotly Technologies Inc., 2019) and visualizes the tap count by the app name with the corresponding app category.

Using stacked bar plots, the temporal distribution of map application usage or app categories was visualized by the hour of the day or the day of the week with `plot_temporal_app_usage`. The session start time was used to group sessions either into 24 hours or the 7 days of the week. If an app was opened shortly before one of the thresholds and crossed it, it was counted only once. This method provided insights into hourly or daily temporal patterns specific to each map application. The function could also be used more generally for all app sessions or category sessions.

To quantify the observed changes and differences, a series of statistical tests were employed. The Kruskal-Wallis test, a non-parametric one-way analysis of variance by ranks, was applied to the map session metrics. This test was conducted using the `stats.kruskal` function from the SciPy library (Virtanen et al., 2020). It assessed the null hypothesis that the population medians across all groups were equal (Kruskal and Wallis, 1952). When the Kruskal-Wallis test revealed statistically significant differences, a post-hoc Dunn's test for pairwise comparisons was conducted. This additional step enabled the identification of specific differences between any two groups (Terpilowski, 2019). For comparisons between two categorical variables, such as context classification and map use (True/False), a χ^2 test of independence was employed (Virtanen et al., 2020). The null hypothesis for this test posited that there was no relationship between the two variables. When this test produced significant results, further analysis was performed to identify categories with notable differences. This involved conducting pairwise χ^2 tests for all combinations within the first category (e.g., the context categories), with a Bonferroni correction applied to account for multiple comparisons (Perktold et al., 2023; Virtanen et al., 2020).

These statistical methods were chosen to provide a comprehensive analysis of the data, facilitating the identification of significant patterns and relationships within the dataset.

Lastly, the primary functions of map apps were determined. Despite being categorized into two groups in the Google Play Store, the categorization only partially aligned with the features of the apps, with similar apps not always placed in the same category. Thus, map apps were manually sorted by their main function to differentiate more clearly between them for clearer differentiation and discussion. We identified the following categories: (offline) navigation, ticket shop, booking of cars and bikes and/or scooters, booking travel plans (hotel, flight, car), information, entertainment, game, flight/airline travel, and sightseeing (see Appendix: Table *8*).

4 Results

This chapter gives an overview of the computations and visualizations performed on the aligned GPS and tap data. The first part presents some descriptive statistics on the data from preprocessing to after the alignment. Subsequently, the chapter is divided into three principal sections that address the research questions specified in section 1.2. The first two sections examine map app usage at the macro level, with and without context. The third section focuses on map app usage at the individual level, comparing two separate users. Keep in mind that staypoints represent stationary mobility, while triplegs correspond to non-stationary mobility.

4.1 Descriptive Statistics

Tap data was collected for 51 participants, while GPS data was obtained from 44 individuals. To perform our analyses, we cross-referenced these datasets, resulting in a final sample of 39 participants with both tap and GPS data available for analysis. During the preprocessing stage, a minor proportion (∼1%) of the GPS data obtained from the 39 participants was removed due to temporal overlaps in the GPS sessions. Furthermore, the elimination of taps in SBB Preview and MapOnTap resulted in a reduction of 1.34% of the total taps recorded. The duration of the study, defined as the time period between the initial and final data entry recorded, exhibited variability between participants. Furthermore, since participants had the option to activate or deactivate GPS tracking at any time, GPS data were not consistently collected for the entire MoT data collection period.

Before alignment, the average study duration for the GPS dataset was 129 days, with a median duration of 56 days. The first quartile of GPS study duration was 10 days, while the third quartile was 208 days. The longest GPS study period recorded for a participant was 737 days (∼2 years). For the tap data, the average study period was 82 days, with a median of 34 days. The 25$^{\text{th}}$ percentile was 7 days and the longest study duration extended to 320 days.

The alignment of GPS data with tap data led to some data loss, primarily because there were instances where no GPS point was collected within 900 seconds. Consequently, significantly more GPS data was lost compared to tap data, with losses amounting to 90.08% and 33.18%, respectively.

Table 2: Phone Usage Duration by State of Mobility and Context Categories

Context	Average Minutes / Day	Total Minutes	Days Used
Mode			
Slow Mobility	716.90	256651.52	358
Fast Mobility	67.47	19768.22	293
Purpose (OSNA)			
Home	81.83	25366.56	310
Work	50.98	12439.18	244
Classified POI Tag (OSM)			
Residential	142.30	48525.40	341
Transportation	58.48	15613.92	267
Food	35.73	7432.82	208
Commercial	21.30	2385.64	112
Education	21.13	2049.98	97
Tourism	16.24	860.58	53
Healthcare	11.74	273.73	18
Entertainment	12.23	207.85	17

An examination of smartphone usage time revealed notable differences in the average time spent on applications based on the state of mobility and context-enriched categories. The mean duration of stationary and non-stationary periods per day was 4 hours and 19 minutes and 12 hours and 52 minutes, respectively. Taking into account the context-enriched states of mobility, the mean daily minutes spent using the phone are illustrated in *Table 2*. Since there were more data for triplegs than for staypoints, and the classification method also impacted how much data was classified for staypoints, the average time spent per day was calculated based on the total number of days with phone use according to the method of context classification of the state of mobility. There were 358 days of data for the triplegs motorization speed, 328 days for the OSNA purpose classification, and 347 days for OSM POI classification.

The classification of staypoints was associated with some data loss, as not all staypoints were successfully classified. The OSNA technique experienced greater data loss compared to the OSM method, averaging just 2 hours and 35 minutes of usable data per day, whereas the OSM method achieved an average of 3 hours and 43 minutes per day. According to the OSNA method, users spent more time on their devices at home (77 minutes / day) compared to at work (37 minutes / day). Similarly, in the OSM method, residential locations showed the highest engagement, with an average of 2 hours and 20 minutes spent per day, followed by transportation (45 minutes / day) and dining (21 minutes / day).

No information was lost in the classification of triplegs by motorization speed. The most significant time commitment occurred at speeds <20 km/h, averaging 11 hours and 57 minutes per day, and only 55 minutes for fast mobility. This comparative analysis highlights the diverse contexts that influence smartphone usage frequency.

Prior to the alignment process, 36 of the 39 participants accessed a map app at least once during the study period. Post-alignment, data from 34 participants with map use remained, of which 31 participants accessed map apps while stationary, and 34 while non-stationary. In total, 54'670 aligned map taps were recorded while stationary out of a total of 773'161, and 191'135 map taps during non-stationary segments from a total of 5'493'132 recorded tap. Thus, the map taps represented for 7.07% and 3.48% of the aligned stationary and tripleg taps, respectively. Across the entire aligned dataset, participants used 68 different map applications, with 45 accessed in stationary states and 67 in non-stationary states.

4.2 Macro-Level Map App Usage: Stationary vs. Non-Stationary Behavior

In response to the first research question, this section presents an overview of map app usage, both stationary and non-stationary, at the macro level, that is, across all participants.

A general trend emerged where map sessions were generally shorter during stationary periods as opposed to non-stationary periods. Participants were also observed to exhibit marginally higher tapping speeds while remaining stationary. Furthermore, both staypoints and triplegs exhibited greater variability in median map session duration (SP SD=1.2; TPLS SD=1.3) compared to the parameter map tap speed (SP SD=0.5; TPLS SD=0.5).

4.2.1 Staypoints

Of the total of 6'814 staypoints, 2'200 included taps within a map app, which is approximately one-third of all staypoints. For these staypoints with map use, the visualizations in this subsection will illustrate when, how, and which map applications were used.

An exponential relationship emerged between the use of map apps and the cumulative number of taps within staypoints indicated by the straight line in the log-scaled barplot (*Figure 5*). Google Maps, categorized under travel and local, accounted for the highest cumulative tap count while stationary, with a total of 22'797 taps. SBB Mobile, from the maps and navigation category, followed with roughly half the number of taps, registering 12'251 taps in total.

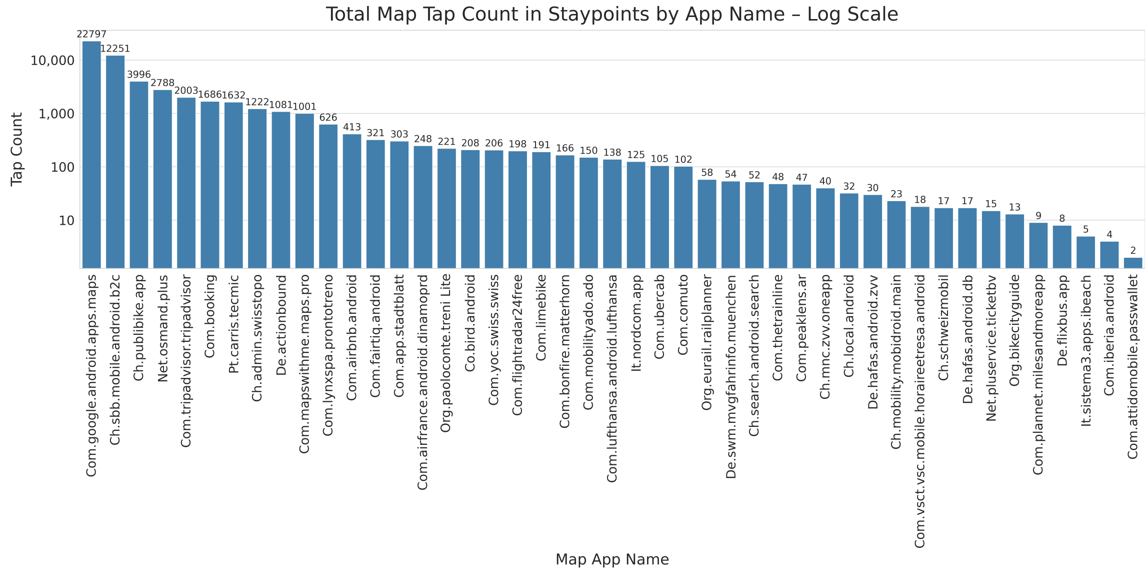


Figure 5: Barplot of Map Tap Count in Staypoints by App Name

The Sankey diagram (*Figure 6*) illustrates the cumulative number of taps for maps apps and the corresponding app category in the Google Play Store. A higher number of apps were accessed in the travel and local category and registered higher tap counts. Publibike recorded 3'996 taps, which constituted one-third of the total recorded by SBB Mobile and ranked third in tap counts. Other apps in the travel and local category varied in their functionality and exhibited tap counts within the tap range of 1'600–2'800. These included the offline navigation app OsmAnd+, the travel planning apps Tripadvisor and Booking, and the ticket shop app for Lisbon Carris. The navigation app swisstopo had 1'222 taps and was ranked second among apps in the maps and navigation category and eighth among all map apps.

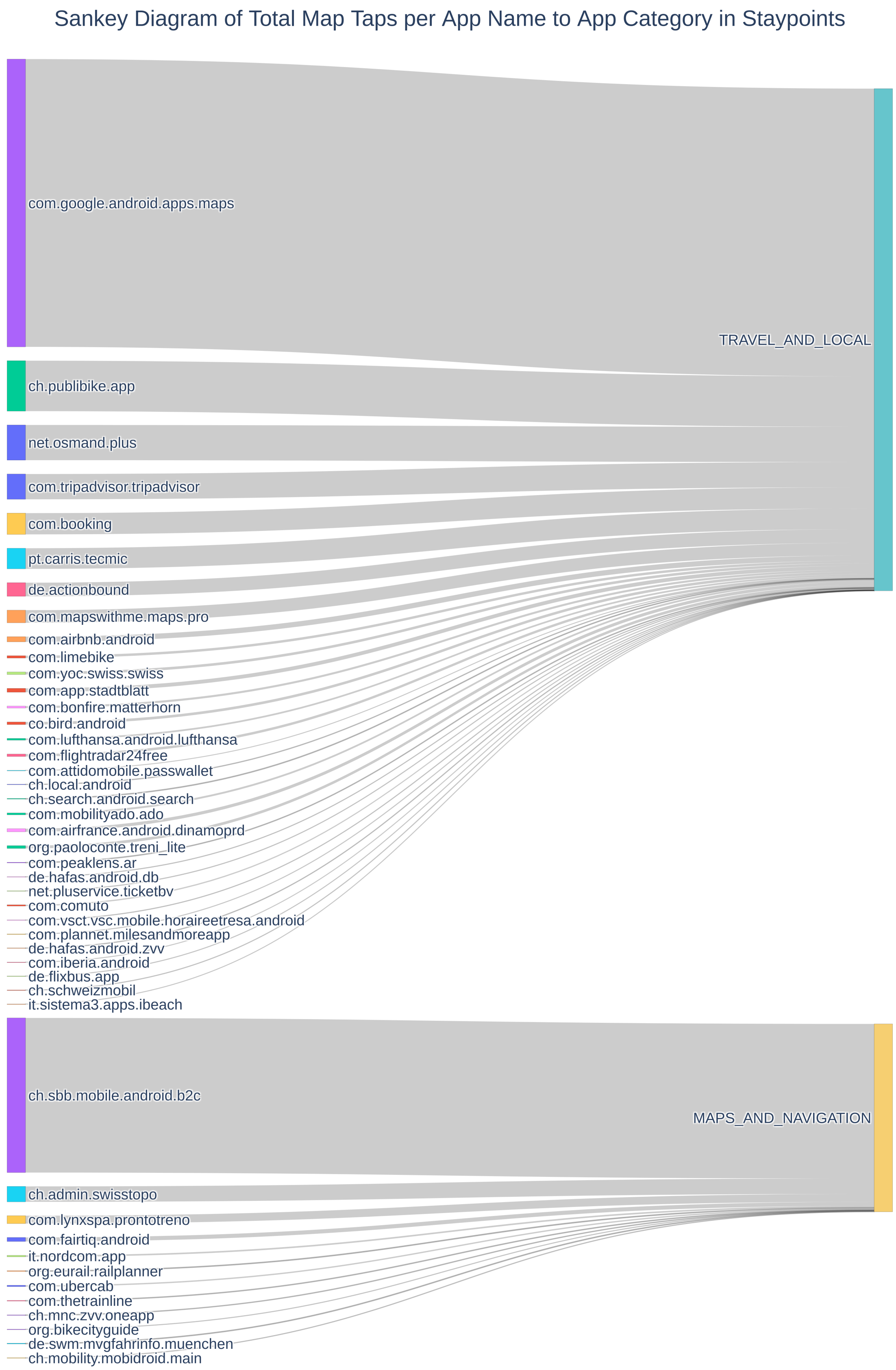


Figure 6: Sankey Diagram of Staypoint Map Apps

Session Metrics

Before presenting the actual values for the duration and tap speed of map sessions, it is important to highlight the discrepancies observed in the number of staypoints with session data, classified by the name of the map application. In terms of staypoints, of the 45 map applications accessed, a total of only eight map applications were accessed at more than 20 staypoints, the remainder falling below this threshold. Furthermore, the session metrics only encompassed 2'099 of the 2'200 staypoints with map usage, as session metrics could only be calculated if there were a minimum of two taps within a session.

Although Google Maps recorded a higher cumulative number of taps in general, there were fewer staypoints in Google Maps (676) than in SBB Mobile (945). The subsequent highest staypoints with map app usage were for Publibike the bike rental app (299), offline navigation apps OsmAnd+ (103) and MAPS.ME (23), swisstopo (41), and the ticket shop apps Fairtiq (52) and Trenitalia (33). The remaining map apps exhibited a markedly lower number of staypoints (<20), with several apps having a single staypoint.

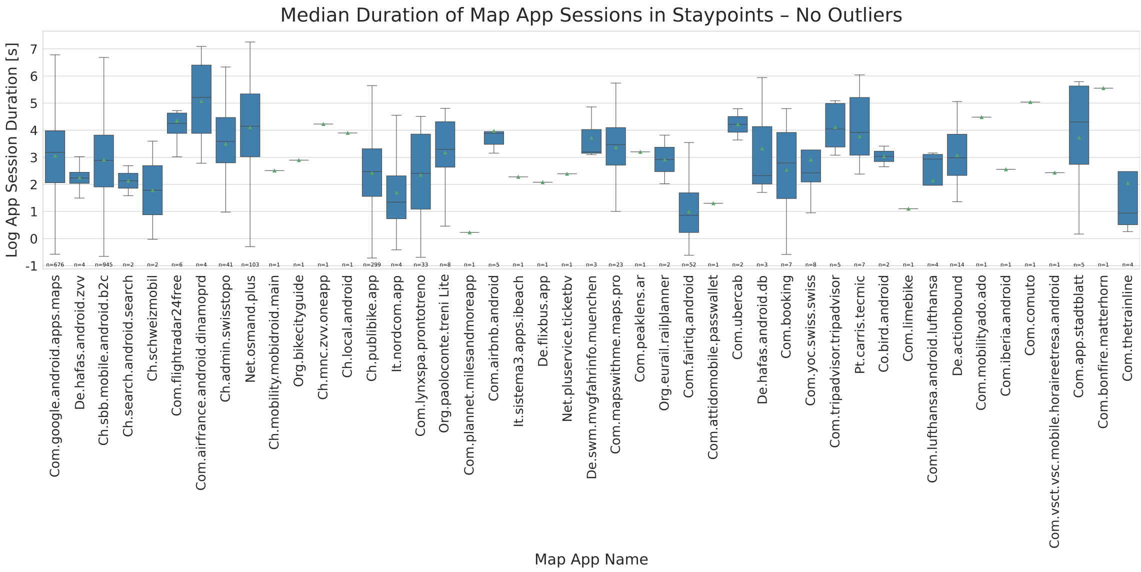


Figure 7: Boxplot of Log Median SP Duration

The distribution of map session duration by app name was visualized with boxplots (*Figure 7*). Additionally, a Kruskal-Wallis was conducted and yielded a p-value<0.001, suggesting that there were statistically significant differences in the median session duration. Subsequently, a post-hoc Dunn's test with a Bonferroni adjustment was performed to check for differences between the map apps (*Table 9*). The findings revealed that the session durations were similar for Google Maps (3.18) and SBB Mobile (2.89), with both values nearing 3. The offline app OsmAnd+ had a significantly higher median session duration (4.15), while other navigation apps like swisstopo (3.58) and MAPS.ME (3.46) exhibited session durations more similar to Google Maps. In contrast, the shortest session durations among navigation apps were observed for SchweizMobil (1.79) and search.ch (2.13), but there was not enough data, with both only having two data points each.

With regard to apps related to public transport ticketing or timetables, a more extensive range of session durations was discerned. However, for a considerable number of apps with longer durations than SBB Mobile, the number of data points was markedly lower, frequently amounting to only one. In addition to SBB Mobile, the only two ticket shop apps with over 10 data points are Fairtiq (0.86) and Trenitalia (2.41), which both had shorter durations than SBB Mobile. Carris (3.92) and Orario Treni (3.29) were found to have longer session durations, with seven and eight staypoints, respectively. Apps with slightly longer session durations, but with much fewer available app session data available (<6 staypoints with map use) tended to be trip planning apps such as Flightradar24Free, Airbnb, Tripadvisor, and AirFrance.

AirFrance stood out with the highest median session duration, exceeding five. Upon closer examination, three AirFrance app sessions with longer durations were identified: 20 minutes, 8 minutes, and just over 1 minute were identified. The shortest session, 16 seconds, occurred in proximity to the 8-minute session, suggesting a possible relation between the two. The tap speed of the 20-minute session fell within the range of the other three sessions and therefore did not appear to be an outlier.

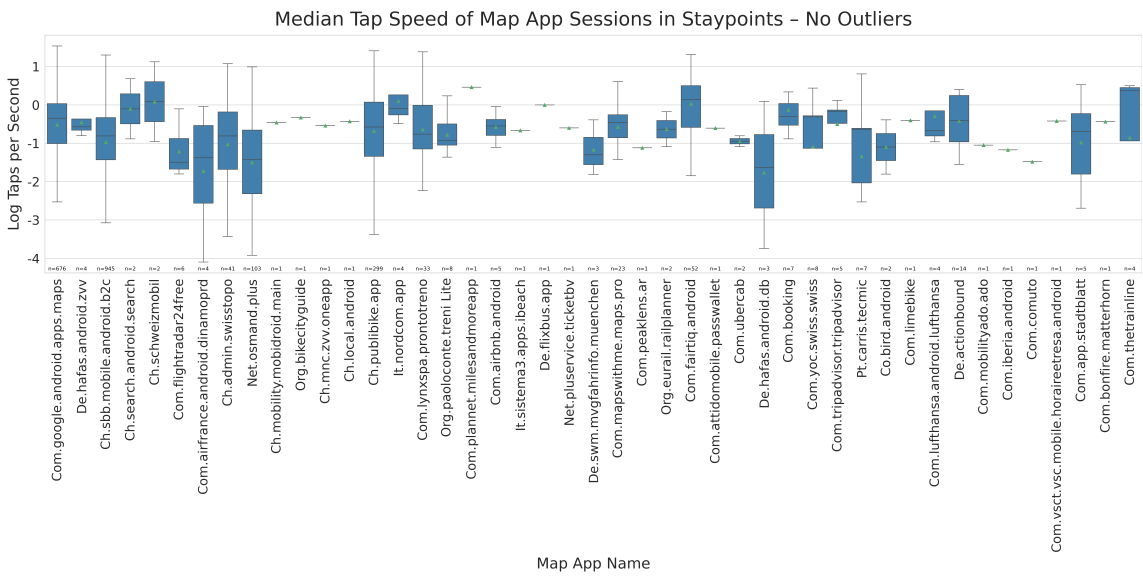


Figure 8: Boxplot of Log Median SP Taps per Second

A Kruskal-Wallis test was performed to examine possible statistically significant differences in the population median of the logarithmic transformed median tap speeds in various map apps (boxplots visualized in *Figure 8*). The null hypothesis, positing that the medians are consistent across all groups, was rejected ($p < 0.05$). Subsequent post-hoc analysis using Dunn's test revealed that Google Maps exhibited a statistically higher tap speed (-0.35) compared to SBB Mobile (-0.81) ($p < 0.001$) (*Table 10*). Among navigation or routing apps, excluding search.ch (-0.10) and SchweizMobil (0.08) due to their limited data entries (n=2 each), several apps demonstrated lower tap speeds than Google Maps. These included MAPS.ME (-0.46), swisstopo (-0.81), and OsmAnd+ (-1.42). However, only the difference between Google Maps and OsmAnd+ reached statistical significance ($p < 0.001$). It should be noted that, despite the larger differences in median values for some applications, not all comparisons yielded statistically significant results. This outcome may be attributed to factors such as smaller sample sizes for certain applications and the inherent variability within groups.

A comparison of ticket shop-related applications with SBB Mobile yielded comparable tap speeds for Eurail (-0.63), Carris (-0.64), Trenitalia (-0.76), and Orario Treni (-0.92). It should be noted that Fairtiq (0.14), Trenord (-0.10), and Trainline (0.37) exhibited noticeably faster tap speeds than MVG Fahrinfo München (-1.30) and DB Navigator (-1.63), which demonstrated slower speeds than SBB Mobile. Of these relationships, only Fairtiq with SBB Mobile returned a significant difference in the post-hoc Dunn's test.

In the case of map apps focused on air travel, the median and mean values were more widely spread, without a discernible pattern with regard to duration. Specifically, Flightradar24Free (-1.49) and AirFrance (-1.38) showed lower median tap speeds compared to SBB Mobile. Conversely, Lufthansa (-0.67) had a median tap speed more akin to that of SBB Mobile, and Swiss (-0.31) exhibited a higher median tap speed, closely aligning with Google Maps. The only map app used during stationary periods for entertainment purposes was Actionbound, which exhibited a tap speed (-0.41) comparable to that of Google Maps.

The only other app to display significant differences in the post-hoc Dunn's test was the bike rental app Publibike. With a median tap speed of -0.58, it had significantly lower tap speeds than SBB Mobile (-0.81) and OsmAnd+ (-1.42), and, unsurprisingly, a faster tap speed than the Fairtiq check-in check-out ticketing app (0.14).

Temporal Map App Access

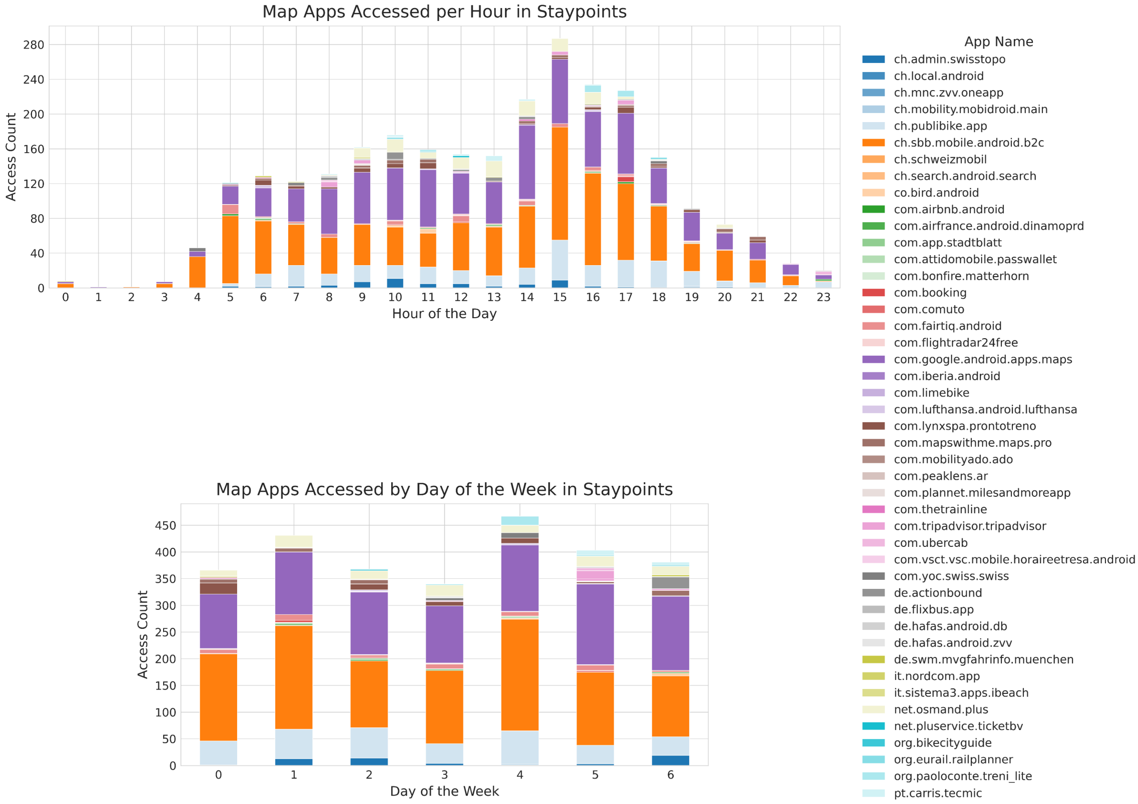


Figure 9: Temporal Access of Map Apps in Staypoints

We examined when each map app was accessed while stationary(*Figure 9*. Map apps were accessed more during the day than at night, with three notable peaks throughout the day. A smaller peak was observed around 6:00, followed by a larger one at 10:00 and another in the middle of the afternoon at 15:00. Furthermore, SBB Mobile saw higher usage than Google Maps from 04:00 to 06:00, 15:00 to 18:00, and 20:00 to 21:00. Among navigation apps, swisstopo highlighted usage throughout the working hours from 8:00 to 16:00, and OsmAnd+, which slightly later between 9:00 and 17:00. Bike rental in Publibike started more early in the day, from 6:00 onward, with a marked increase at 15:00 and consistent use until 19:00. Fairtiq experienced the highest use in the early morning between 5:00 and 6:00, gradually decreasing usage until noon, with some activity continuing into the afternoon.

Throughout the week, map apps were accessed most on Mondays and Thursdays, with Wednesdays showing the lowest activity. On these days, SBB Mobile had the highest access count, with the minimum on Sunday. This differed from Google Maps, which saw the most usage on Fridays, closely followed by Saturdays, with Sunday again being the day of least usage. Fairtiq had slightly higher use on weekdays than on weekends. The game Actionbound was accessed mainly on Saturday. Tripadvisor was accessed most often on Fridays, while Uber on Fridays and Saturdays.

4.2.2 Triplegs

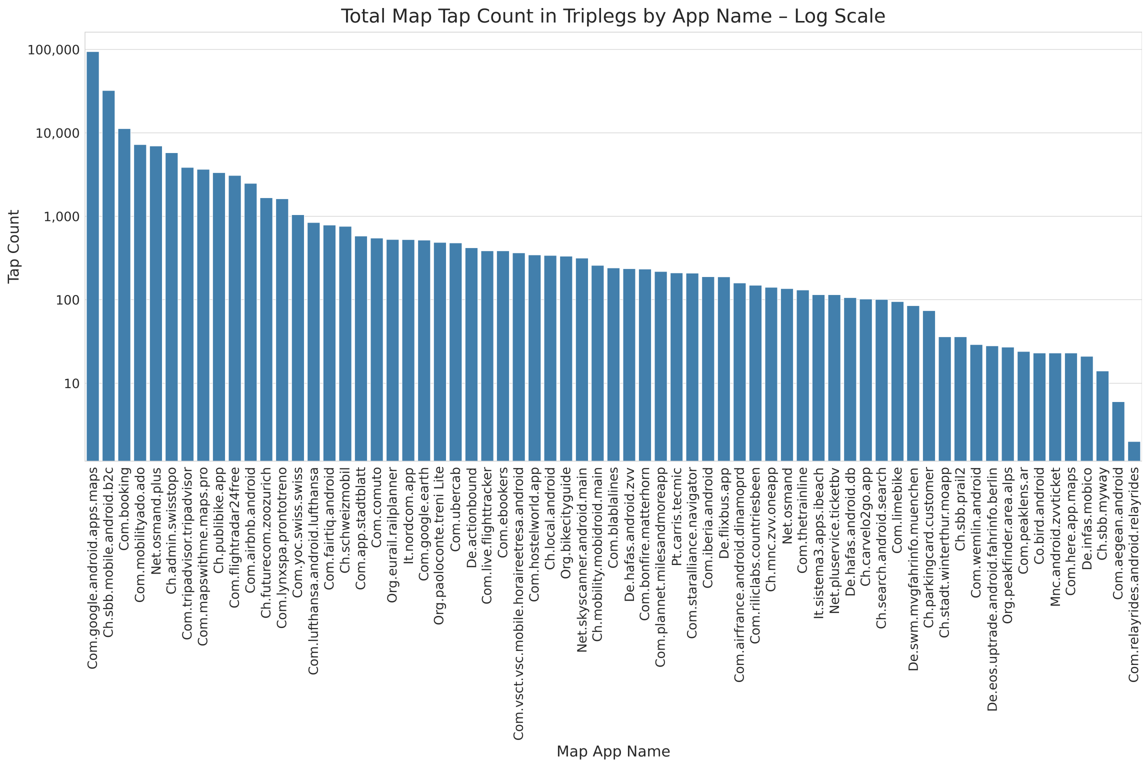


Figure 10: Barplot of Map Tap Count in Triplegs by App Name

Of the total of 20'026 triplegs, only one fifth involved access to map apps (3'842). Similarly to the pattern observed in staypoints, an exponential relationship was identified between the cumulative tap count per map app name (*Figure 10*).

In the Sankey diagram, Google Maps and SBB Mobile had the highest tap counts, with 94'275 and 32'194 taps, respectively (*Figure 11*). Booking, which ranked only sixth in staypoints, held the third-highest tap count in triplegs with 11'226 taps. ADO Boletos de Autobús, which was rarely used while stationary, ranked fourth in tripleg tap counts with 7'237 taps. Other map apps with high cumulative tap counts in both staypoints and triplegs included the navigation apps OsmAnd+ (6'952) and swisstopo (5'779). Given the higher total number of taps in triplegs compared to staypoints, several apps, such as Tripadvisor (3'855), MAPS.ME (3'655), and Publibike (3'337), fell within the tap count range of 4'000 to 10'000. Apps with higher tap counts while non-stationary than in staypoints included Airbnb, Zoo Zürich (only in triplegs), as well as the flight apps Flightradar24Free, Swiss, and Lufthansa.

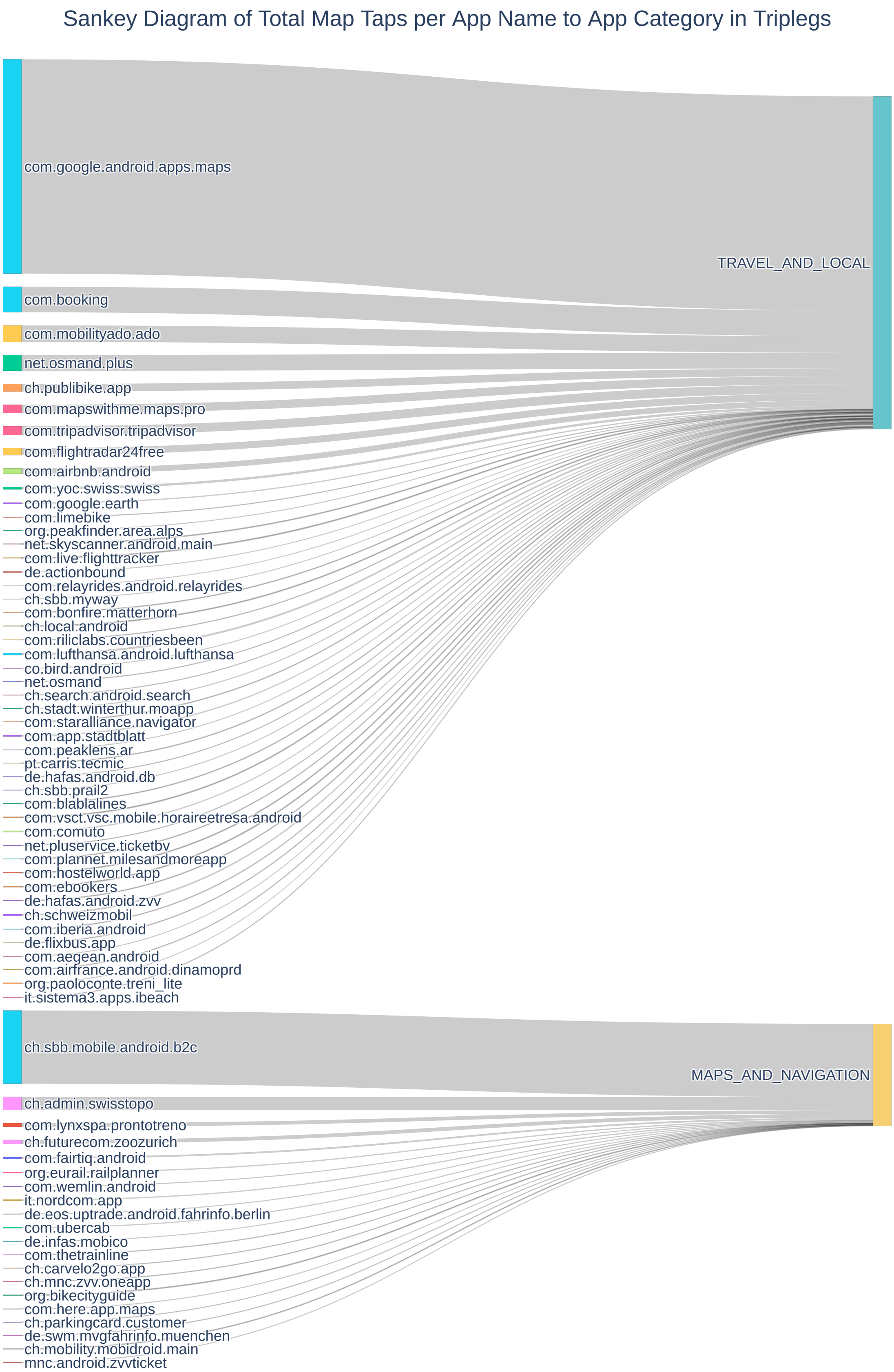


Figure 11: Sankey Diagram of Tripleg Map Apps

Session Metrics

Similarly to staypoints, a Kruskal-Wallis test was performed for the tripleg session duration data and returned a p-value<0.001. Consequently, a post-hoc Dunn's test was done to show differences between the individual apps (*Table 11*). The boxplots of the median duration of map sessions in *Figure 12* revealed that Google Maps sessions were significantly longer (3.73) compared to SBB Mobile sessions (3.24), while both had a comparable IQR. In particular, all navigation apps with more than 10 triplegs that involved map app use exhibited longer session durations than Google Maps. These include MAPS.ME (3.88), swisstopo (4.34), and OsmAnd+ (4.51). Three apps exhibited shorter durations: search.ch (3.65) and Bike Citizens (3.65) with slightly shorter times than Google Maps, and HERE WeGo much slower with a value of 1.66, although this was based on one tripleg. OsmAnd (5.82), SchweizMobil (5.47), and Zoo Zürich (5.20) had the longest median durations, albeit with fewer than five data points each.

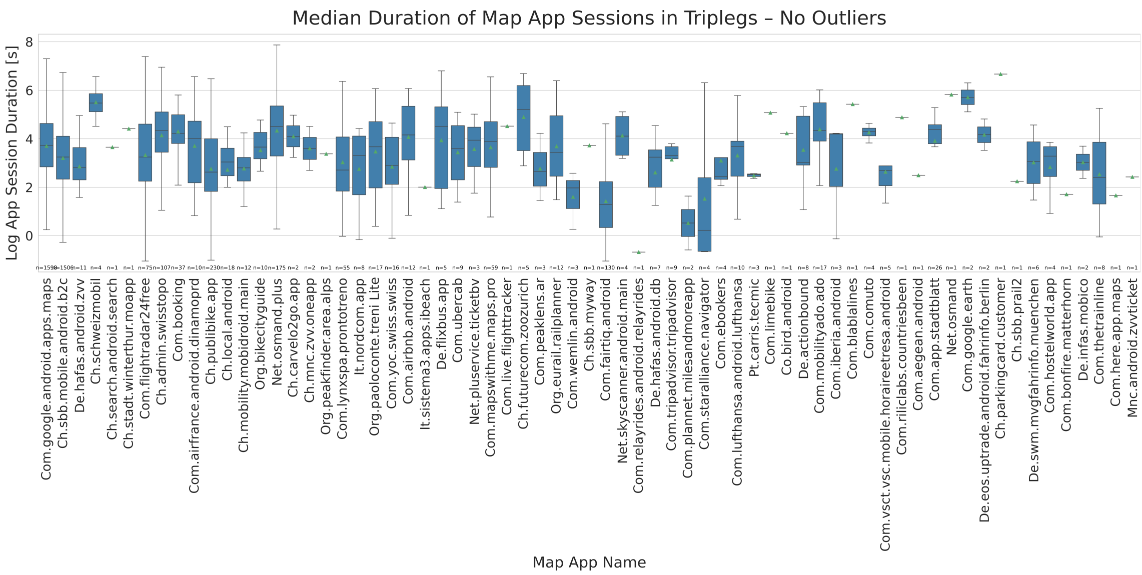


Figure 12: Boxplot of Log Median TPLS Duration

The range of ticket shop apps was slightly broader, with Fairtiq exhibiting the minimum session duration (1.29) and Flixbus displaying the maximum (4.52), while SBB Mobile occupied the middle ground. It is important to note that most ticket shop apps had fewer than 10 data entries, except for four apps: Trenitalia (2.71) and Fairtiq (1.29) with shorter durations, but more than 50 data entries, and ADO Boletos de Autobús (4.34) and Orario Treni (3.67) with longer durations, but only with 17 data points each.

Among the apps with the shortest median durations, the car rental app Turo, formerly RelayRides, had by far the lowest score (-0.68), followed by the airline apps

Miles & More (0.52) and Star Alliance (0.22), although all had four or fewer data points.

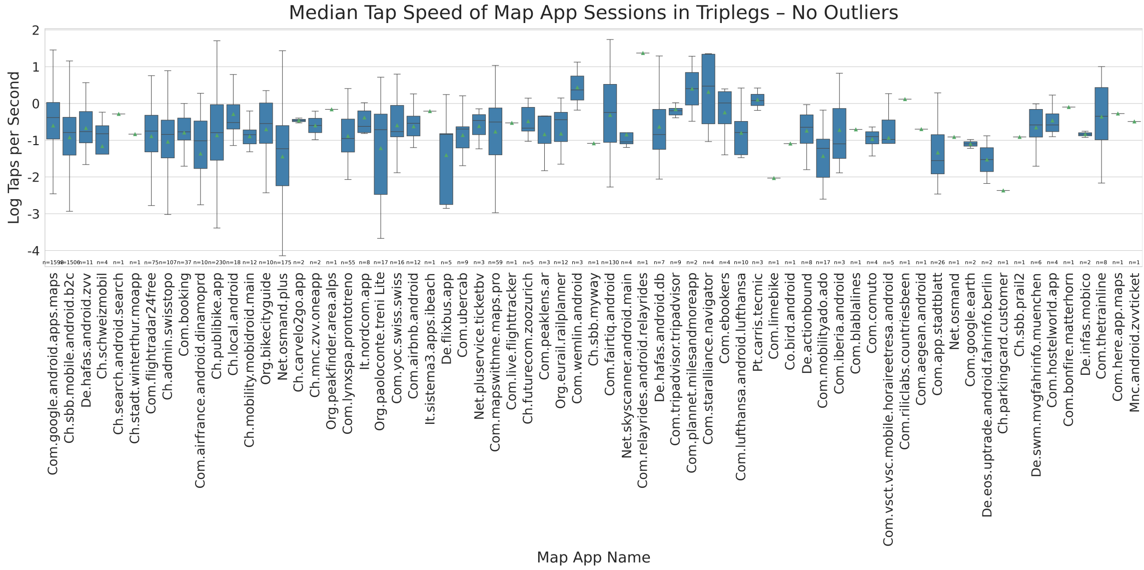


Figure 13: Boxplot of Log Median TPLS Taps per Second

Figure 13 illustrated that the median tap speed for Google Maps (-0.38) was twice as fast as that of SBB Mobile (-0.79), closely resembling the trends observed in staypoints. In examining other navigation apps, only HERE WeGo (-0.28) and search.ch (-0.29) demonstrated slightly higher speeds than Google Maps, though both had only one data entry. The offline navigation app MAPS.ME recorded a slightly slower tap rate (-0.50), while OsmAnd and OsmAnd+ exhibited the slowest speeds at -0.91 and -1.23, respectively. Apps with tap speeds close to that of SBB Mobile included Bike Citizens (-0.55), SchweizMobil (-0.83), and swisstopo (0.84). Turo recorded the fastest tap speed by far (1.37), although this was based on a single data entry. The airline apps Star Alliance and Miles & More exhibited the next-fastest speeds. Among apps with more than ten triplegs, Fairtiq had the highest tap speed (-0.24), which was comparable to the faster tap speeds of navigation apps. Interestingly, no clear trend emerged in terms of which app category had the slowest tap speeds. The six apps with the lowest tap speeds spanned a diverse range of map app functions. However, these apps were observed to have a tendency to display longer session durations.

A Kruskal-Wallis test was performed to ascertain whether the data originated from a common distribution, as was done for the staypoints. As a result of this significant outcome, a post hoc Dunn's test was subsequently conducted ((*Table 12*). In the case of navigation apps, statistically lower median tap speeds ($p < 0.001$) were observed for Google Maps (-0.38) and both swisstopo (-0.84) and OsmAnd+ (-1.23). Furthermore, a notable discrepancy was evident between the offline map apps MAPS.ME (-0.50) and OsmAnd+ (-1.23), with a slightly higher p-value of 0.05. Additionally, the median tap speed of Google Maps was significantly higher than the ticket shop apps SBB Mobile ($p < 0.001$) and ADO Boletos de Autobús ($p < 0.05$), the bike rental app Publibike (-0.79), and the city information app Stadtblatt (-1.55). Moreover, SBB Mobile exhibited a significantly lower tap speed than Fairtiq ($p < 0.01$).

Temporal Map App Access

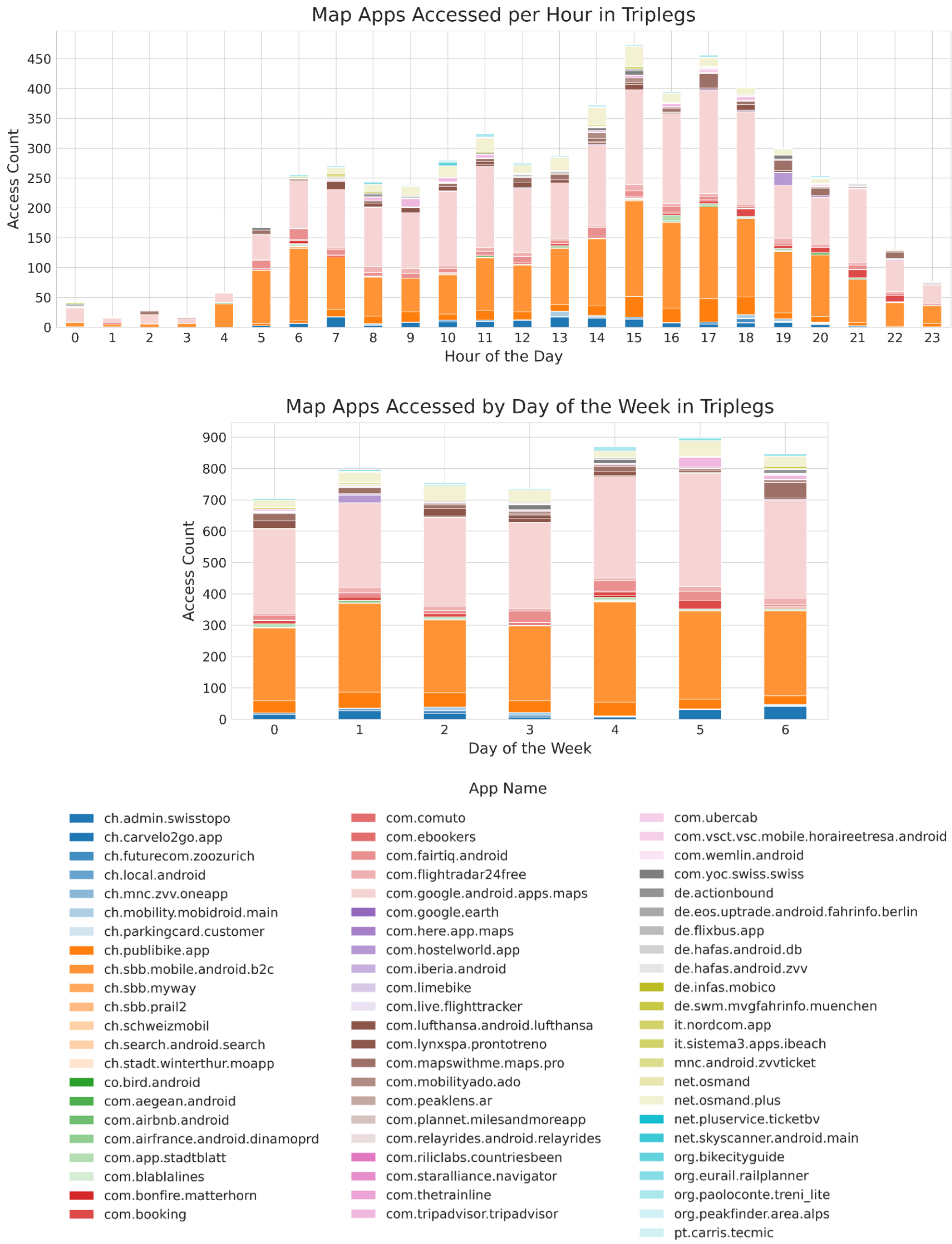


Figure 14: Temporal Access of Map Apps in Triplegs

Similarly to staypoints, we also visualized the temporal aspect of map app access *Figure 14*. The access patterns of map apps throughout the day show a large variation, with usage increasing dramatically in the morning from 5:00 to reach a small peak around 7:00. After a decrease until 9:00, a steady rise continued until 11:00. Usage dipped slightly during lunchtime, followed by an increase to the daily maximum at 15:00. A brief drop occurred at 16:00, followed by another increase at 17:00, after which access steadily declined into the night.

SBB Mobile was accessed more frequently than Google Maps during the early morning hours from 4:00 to 6:00, after which both apps were used at similar rates, if not slightly less, until noon. Fairtiq saw its highest usage in the morning between 6:00 and 7:00, as well as in the afternoon from 14:00 to 17:00. Publibike, the bike rental service, experienced an increased use starting slightly later in the morning around 7:00 than in staypoints, with consistent use until the early afternoon, followed by another increase from 15:00 to 18:00. Car rentals through Mobility Swiss were less noticeable in the morning, peaking at 13:00 with some activity between 18:00 and 20:00.

The offline navigation app OsmAnd+ was accessed throughout the day with taps from 9:00 to 16:00, while MAPS.ME was accessed later, between 17:00 and 19:00. Travel booking apps tended to be used in the evening, with Booking accessed primarily after 18:00, and Airbnb saw the most use around 20:00.

When examining usage by day of the week, access to map apps increased significantly on Mondays and Fridays, while lower activity was observed on Sundays and Wednesdays. Vehicle rental and reservation apps were used more during the workweek, Publibike accessed more from Monday to Thursday, and Mobility Swiss used more on Tuesdays and Wednesdays. Fairtiq was used throughout the week, but the most frequently during the week, particularly from Wednesday to Friday. SBB Mobile had the lowest usage on Sundays and Wednesdays, with the highest tap count on Thursdays, closely followed by Mondays and Fridays. Google Maps saw the highest usage on Fridays, with the lowest activity on Sundays and Wednesdays.

4.3 Macro-Level Map App Usage with Context Enrichment

This section presents the results to answer research question number two about the usage behavior of map apps with regard to context enrichment of the states of mobility. Since the context data are of categorical nature, the map app metrics were applied to the subgroups of staypoints and triplegs and visualized in Marimekko charts and Sankey diagrams.

4.3.1 Staypoints with Function Tags

For the classification of staypoints, three methods were applied: the frequency and OSNA method (both already implemented in the TI library), and POI extraction from OSM. Since the frequency and OSNA methods yielded very similar results, only the results from the more complex OSNA and OSM methods are presented.

4.3.1.1 OSNA Method

The OSNA method employs a two-category classification system for staypoints, whereby the locations are categorized as either "home" or "work". Across all staypoints, regardless of map app usage, a total of 2'129 staypoints were classified with a purpose, accounting for 31.24% of the stationary dataset. Of these classified staypoints, 34.21% were designated as work and 65.79% were designated as home. The OSNA method found the work context for 35 unique individuals and the home context for 29 participants.

A total of 703 staypoints had map app usage and were assigned a purpose category, which accounted for 31.95% of all staypoints with map usage or 10.32% or all staypoints. For the staypoints with map use, a total of 35.56% belonged to the work category and the rest were home locations (*Figure 15*). The access of map apps exhibited a high degree of homogeneity between home and work staypoints, with 33.66% and 31.93%, respectively. This finding was corroborated by a χ^2 test of independence with a p-value of 0.4418, indicating that there was no statistically significant association between the purpose and the access of map apps in staypoints at the macro level.

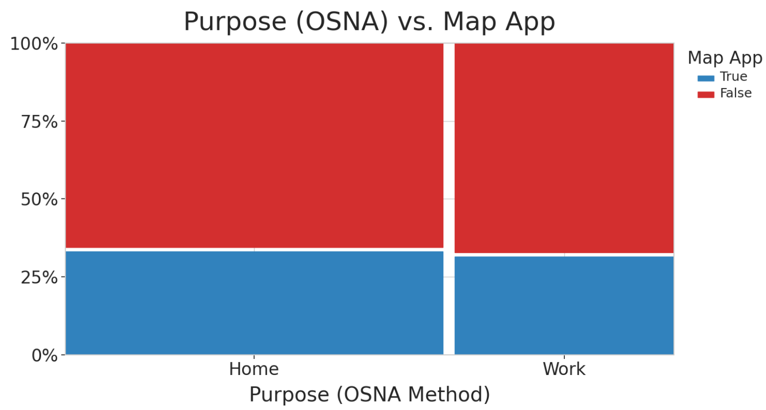
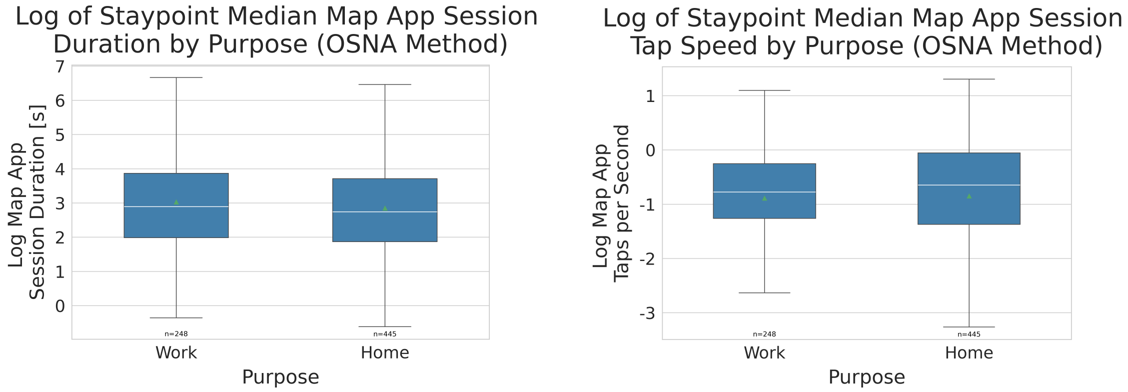


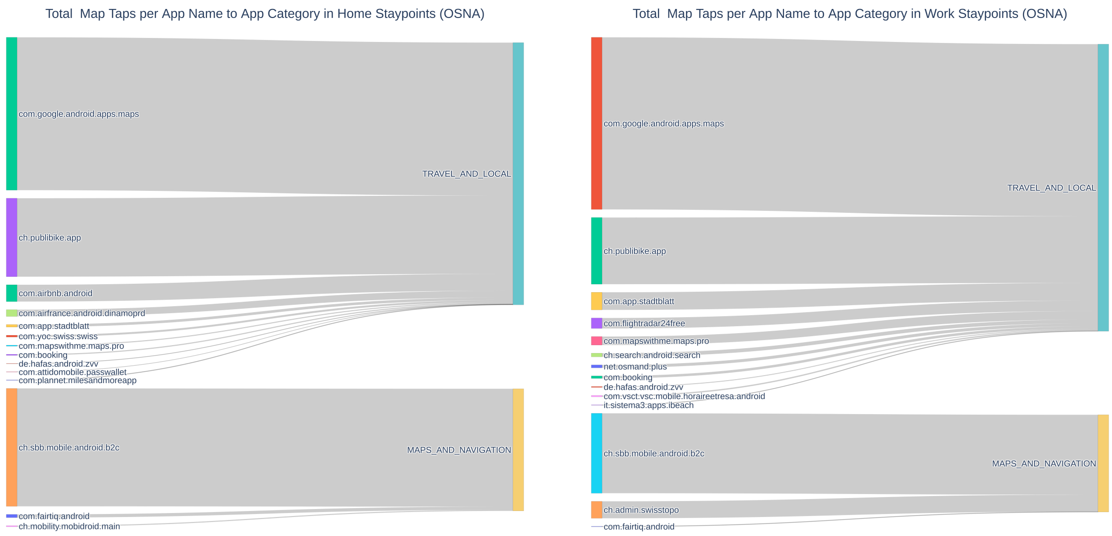
Figure 15: Marimekko Chart of SP Map/No Map Use by Purpose (OSNA)

For the session metrics depending on the home and work category, only 693 staypoints were taken into account due to the loss of some staypoints with a single tap in a session. Upon examination of the session metrics through boxplots (*Figure 16*, only minor differences were observed. The logarithm of the median duration of the map app session was slightly higher for workplace staypoints, with an IQR that remained nearly identical between the two categories. The median tap speed was marginally lower at the work sites and showed a smaller IQR. A Kruskal-Wallis test indicated that these differences were not statistically significant, with p-values of 0.14 for session duration and 0.19 for tap speed.



(a) *Median map duration (log scale)* (b) *Median taps per second (log scale)*

Figure 16: Boxplots of Tap Metrics for Staypoint by Purpose (OSNA)



(a) *Home (OSNA Method)* (b) *Work (OSNA Method)*

Figure 17: Sankey Diagram of Map Taps depending on Purpose Category (OSNA)

To check which map apps were accessed depending on the context, we visualized the total number of map taps by context category in the Sankey diagrams *Figure 17*. At home, three apps were used from the maps and navigation category: the SBB Mobile ticketing app with by far the most taps, followed by the Fairtiq check-in check-out app and the vehicle reservation app Mobility Swiss. In the travel and local category, Google Maps showed substantial taps, as well as the bike rental app Publibike. There was also use of travel booking apps like Airbnb and Booking, as well as flight travel apps including AirFrance, Swiss and Miles & More. In the workplaces, we also observed that Google Maps had the highest tap count. However, Swissstopo recorded the second-highest tap count in the maps and navigation category and only very few taps in Fairtiq. In the travel and local category, once again, Google Maps had the most taps, followed by Publibike. Compared to home locations, fewer taps were recorded in flight apps and only in Flightradar24. However, there was a larger variation of navigation apps, including MAPS.ME, search.ch, and OsmAnd+.

4.3.1.2 OSM Method

Using the OSM method, 85.10% of staypoints (with and without map use) were assigned to a POI. Of the 5'799 staypoints, 57.75% were classified as residential, 25.54% as transportation-related and 9.16% as food-related.

Table 3: Ratio of Reoccurring Locations by OSM Classification of Staypoints

	Staypoints Regardless of Map Use			Staypoints with Map Use		
OSM Classification Tag	**Recurring Location**	**Total Staypoints**	**Ratio of Recurring Locations**	**Recurring Location**	**Total Staypoints**	**Ratio of Recurring Locations**
Residential	279	3'349	8.33%	93	1'231	7.55%
Transportation	76	1'481	5.13%	42	508	8.27%
Food	32	531	6.03%	8	144	5.56%
Commercial	30	189	15.87%	11	55	20.00%
Education	12	146	8.22%	4	42	9.52%
Tourism	5	60	8.33%	2	22	9.09%
Entertainment	1	19	5.26%	0	10	0.00%
Healthcare	1	24	4.17%	0	2	0.00%
Total	**436**	**5'799**	**7.52%**	**160**	**2'014**	**7.94%**

A total of 2'014 staypoints with map use were context-enriched, representing 91.55% of the map staypoints and 29.56% of all staypoints. In the case of staypoints with map use, the three most prevalent POI categories were also residential (55.95%), related to transportation (23.09%) or food (6.55%). The order of the most popular OSM classification tags remained relatively consistent when comparing stationary data with and without map use. The only exception was for categories with minimal data, namely entertainment (2 SP) and healthcare (10 SP) (see *Table 3*). Furthermore, the commercial category demonstrated the highest recurrence rate at the specified location. Specifically, 20% of the commercial staypoints with map use and 15.87% without map use are located in the same place.

We also analyzed context-enriched staypoints by map session duration and tap speed. There were 1'938 staypoints for which metrics could be computed (>1 tap

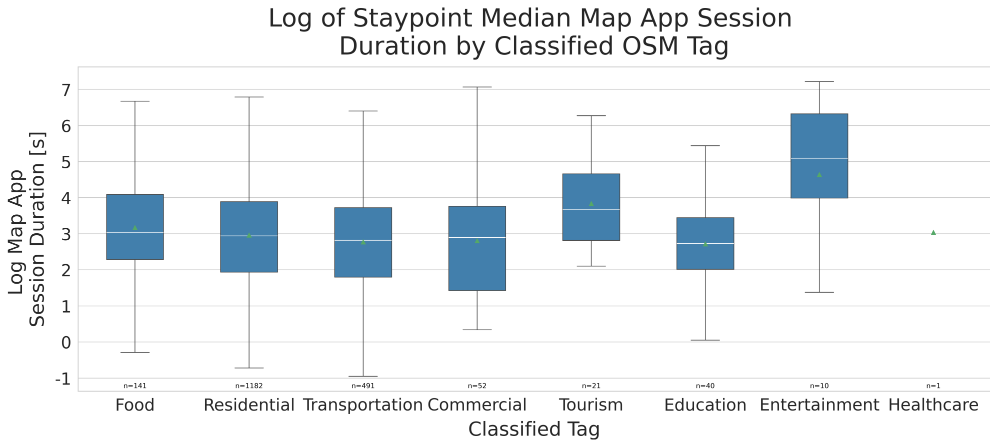


Figure 18: Boxplot of Log Median SP Map Session Duration with OSM Classification

per session). The analysis of the map session duration revealed that staypoints classified as entertainment had the longest session duration, with a median value of approximately 5 (*Figure 18*). Additionally, the median duration of the trip was slightly longer (3.7). The remaining categories exhibited slightly lower medians, approximately 3, except for places of transportation (2.8) and education (2.7). In terms of IQR, the data indicated a tendency for values to fall within the range of 1.8, with the commercial and entertainment categories showing an IQR of approximately 2.33 and healthcare displaying an IQR of 0. A Kruskal-Wallis test confirmed a statistically significant difference in the session duration distributions ($p = 0.002$). However, a subsequent post-hoc Dunn's tests did not identify any statistically significant pairwise differences. The lowest p-values were observed between tourism and transportation ($p = 0.068$), and between entertainment and transportation ($p = 0.071$).

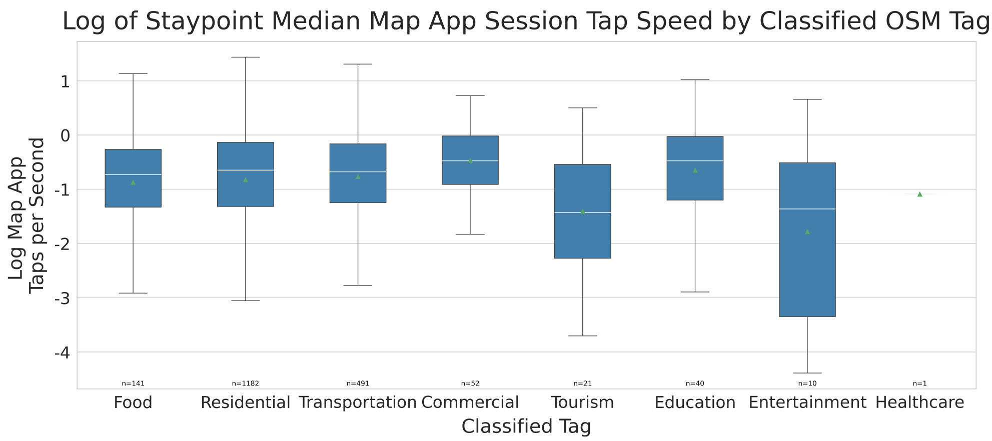


Figure 19: Boxplot of Log Median SP Map Tap Speed with OSM Classification

For tap speed, POI classes for tourism and entertainment showed the lowest median tap speeds, around -1.4 (*Figure 19*). Residential and transportation had similar median tap speeds of -0.65 and -0.68, respectively, while food-related staypoints had a median of -0.73. The IQR was lower for tap speed than duration, with values near one for most categories, except for tourism, which exhibited a higher IQR of 1.73 and entertainment at almost triple the value with 2.84. Assuming a level of significance $\alpha = 0.05$, the Kruskal-Wallis test returned a significant difference for tap speed ($p = 0.02$). A post-hoc Dunn's tests revealed that the null hypothesis, i.e., no significant differences between the groups, was only rejected for the relationship between the commercial and tourism groups ($p = 0.03$). For all other pairwise comparisons, we failed to reject the null hypothesis.

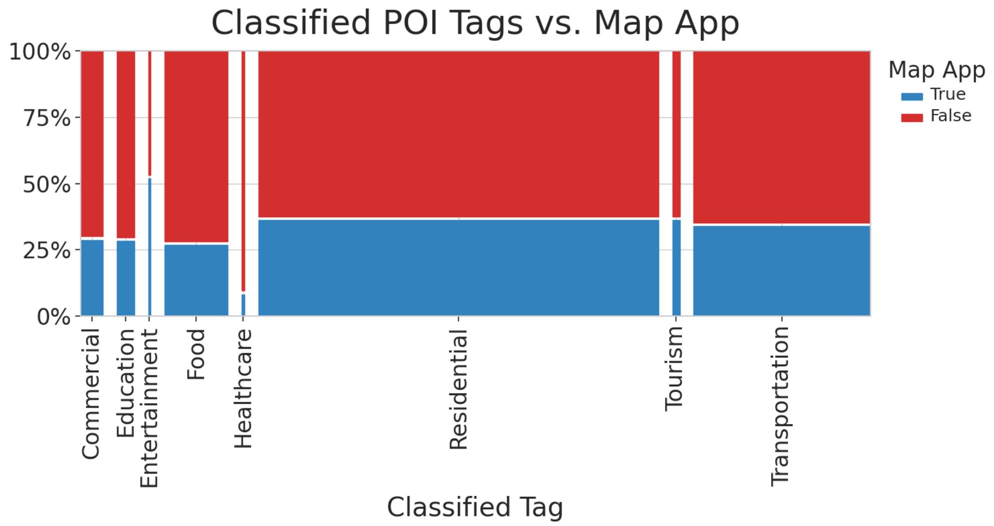


Figure 20: Marimekko Chart of SP Map/No Map Use by OSM Classified Tags

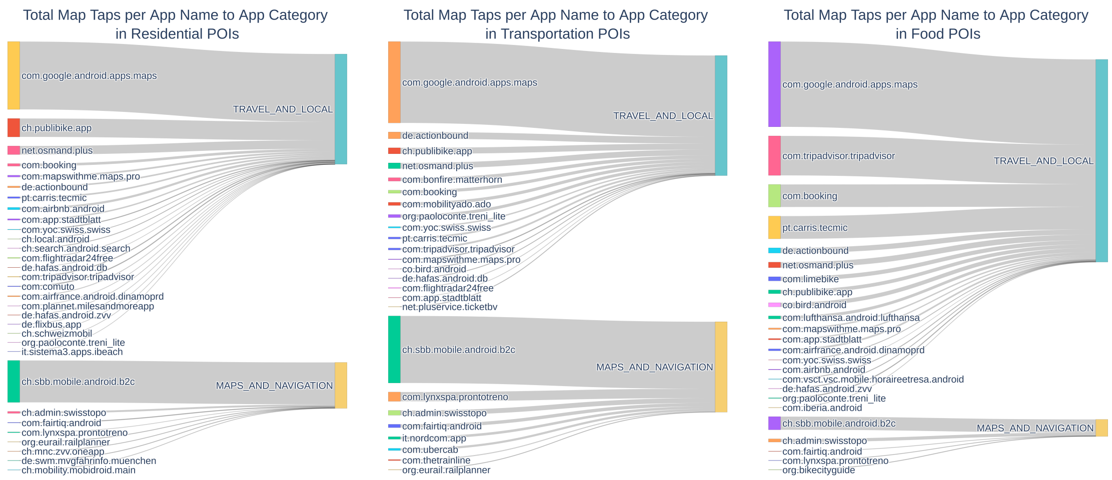
The Marimekko chart in *Figure 20*, which illustrated the relative proportion of staypoints with map use, indicated that staypoints categorized as residential, touristic, and transportation exhibited the highest relative map use, accounting for approximately 35%. The POI categories of food, commerce, and education POIs demonstrated marginally less relative map usage, close to 28%. The most extreme values were observed for entertainment locations (52%) and healthcare (8%). A χ^2 independence test indicated that there was a relationship between POI classification and map use ($p < 0.001$). A follow-up pairwise χ^2 test of independence with the Bonferroni adjustment revealed that only the residential and food categories exhibited statistically significant differences. Without the Bonferroni correction, a greater number of relationships were identified as statistically significant (see *Table 4*).

The Sankey diagrams in *Figure 21* illustrate the map apps in the three most frequently used categories. For residential POIs, Google Maps had the highest tap count, followed by SBB Mobile, Publibike, and OsmAnd+. Other map apps showed considerably lower tap counts. In transportation-related POIs, Google Maps and SBB Mobile still had the highest tap counts, but the gap was smaller. We also note that ticket shop apps were more common than in residential or food areas, and included the apps ADO Boletos de Autobús, Carris, Orario Treni, Ticket bus Verona,

Table 4: POI Pairwise χ^2 Independence Test Results with Bonferroni Correction

Category 1	Category 2	χ^2 Statistic	p-value	Degrees of Freedom	Bonferroni Corrected p-value
residential	food	18.19	0.00002	1	0.000719
residential	commercial	4.21	0.04023	1	1
residential	healthcare	7.12	0.00762	1	0.274313
food	transportation	8.88	0.00288	1	0.103768
food	entertainment	4.72	0.02973	1	1
transportation	healthcare	6.00	0.01433	1	0.515975
healthcare	tourism	5.43	0.01983	1	0.714019
healthcare	entertainment	8.26	0.00406	1	0.146001

DB Navigator and Trenitalia. Interestingly, in the maps and navigation category, Trenitalia had more taps than swisstopo, which differed from results observed without context (*Figure 6*). Finally, for food-related POIs, there was a slight shift in map apps with the highest tap counts. While Google Maps still led, Tripadvisor, Booking, and Carris from the travel and local category had more taps than SBB Mobile from the maps and navigation category. Vehicle reservation apps such as Lime, Bird, and Publibike were used at similar rates and had higher tap counts than in the other two POI categories.



(a) *Residential* (b) *Transportation* (c) *Food*

Figure 21: Sankey Diagram of Map Taps in Top 3 OSM Categories by App Name and App Category

4.3.2 Triplegs with Mode of Transport

Unlike the two context enrichment methods for staypoints, all triplegs were assigned to either slow or fast mobility categories. The majority of triplegs (87.14%) had an average speed of less than 20 km/h, categorizing them as slow mobility, while the remainder were identified as fast mobility. Among the 3'842 triplegs involving map app usage, 77.85% were designated as slow mobility, and 22.15% fell under the fast mobility category. The Marimekko chart visualized that the relative proportion of triplegs with map app use was higher for fast mobility than for slow mobility (*Figure 22*). Specifically, 33.04% of the triplegs in the fast mobility category involved the use of maps, compared to only 17.14% for slow mobility. A χ^2 test of independence finds a statistically significant relationship between motorization speed and map app access ($p - value < 0.001$).

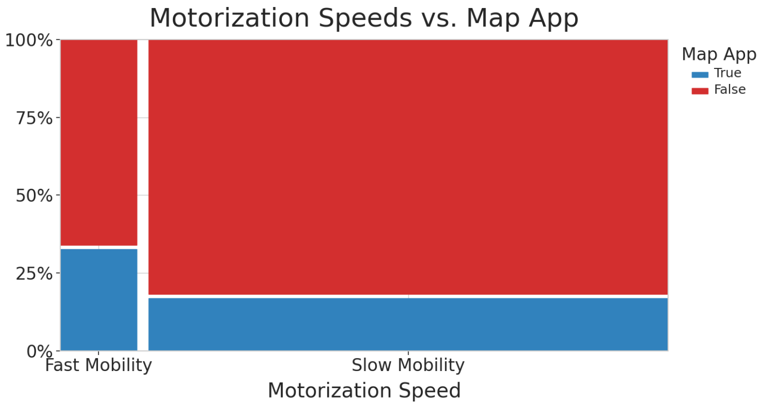
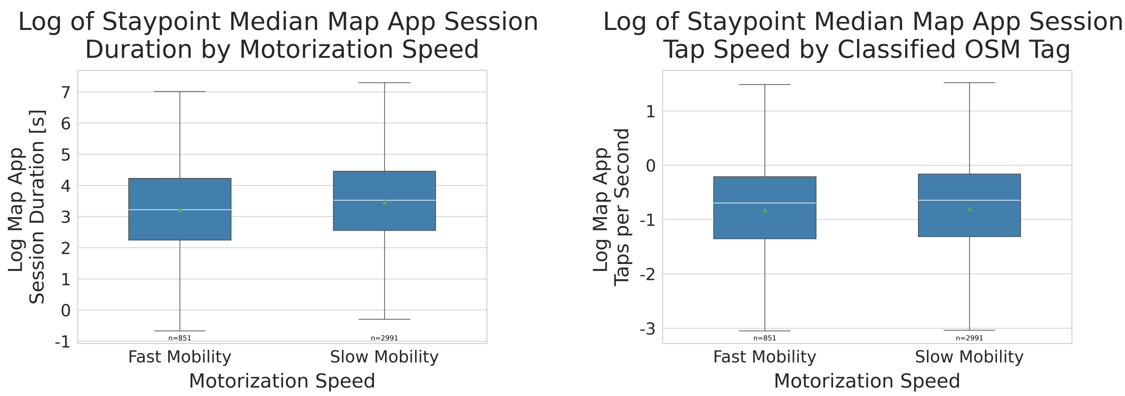


Figure 22: Marimekko Chart of TPLS Map/No Map Use by Motorization Speed

Focusing on the map session metrics of the context-enriched triplegs, a total of 3'827 triplegs were taken into account. For the map session duration, slow mobility indicated a slightly higher median than fast mobility (3.52 vs. 3.22), though the IQR was similar (1.90 vs. 1.98) (see *Figure 23 a*). For tap speed, the two categories were more similar, with a median of -0.64 for slow mobility and -0.70 for fast mobility, and an IQR of 1.15 and 1.14, respectively (*Figure 23 b*). These findings aligned with the results of the Kruskal-Wallis test, which revealed a significant difference in the median for session duration ($p < 0.001$), but not for tap speed ($p = 0.28$).



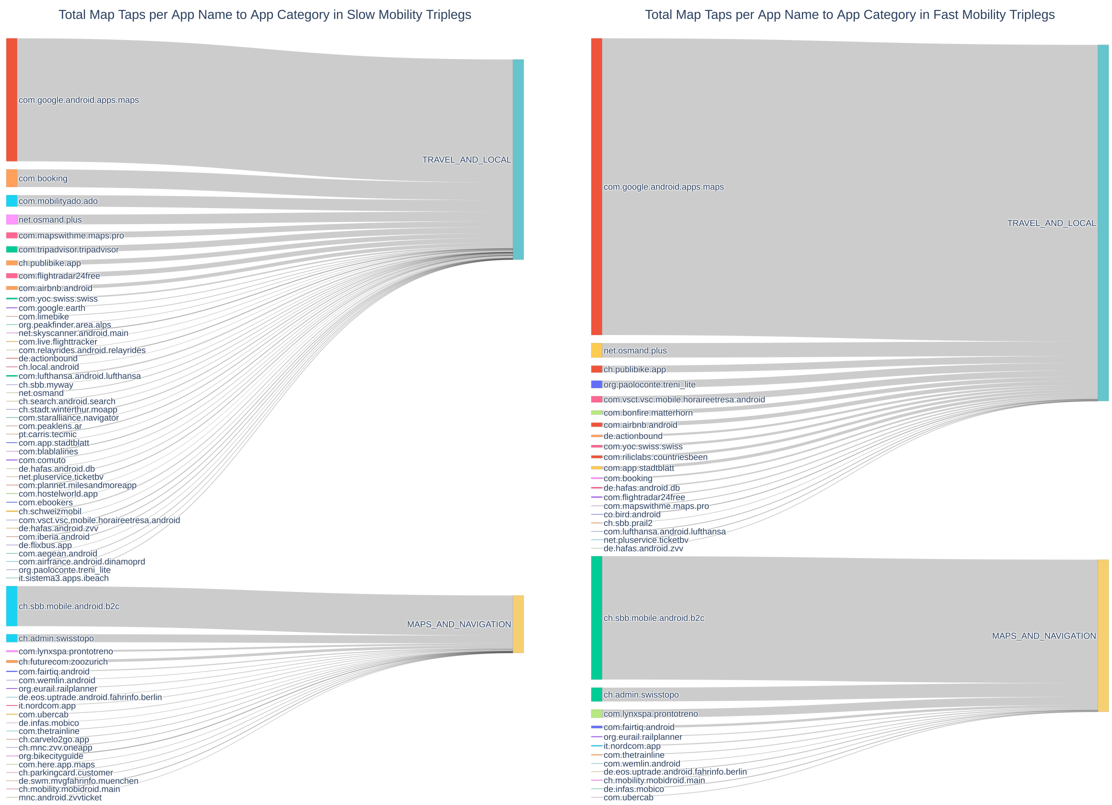
(a) *Median map duration (log scale)* (b) *Median taps per second (log scale)*

Figure 23: Boxplots of Tap Metrics for Tripleg Motorization Speeds

When examining which map apps were accessed during non-stationary periods at high speeds, Google Maps registered the highest tap count, followed by SBB Mobile (*Figure 24 a*). All other apps showed much lower tap counts, with OsmAnd+,

and swisstopo showing similar levels of usage, followed by Trenitalia, Publibike, and Orario Treni. There were three apps related to flight and airlines—namely Lufthansa, Swiss and Flightradar24Free—which had very few taps. Booking and Airbnb were the only map apps used to book travel plans.

For triplegs of slow mobility, a wider variety of map apps was used (*Figure 24 b*). Google Maps still had the highest tap count, followed by SBB Mobile. In the travel and local category, popular apps included Booking, ADO Boletos de Autobús, OsmAnd+, MAPS.ME, Flightradar, Publibike, Tripadvisor, and Airbnb. Within the maps and navigation category, swisstopo and Zoo Zürich had slightly higher tap counts compared to other apps.



(a) *Slow Mobility* (b) *Fast Mobility*

Figure 24: Sankey Diagram of Map Taps in Triplegs by Motorization Speed

4.4 Micro-Level Map App Usage

In addition to a macro-level comparison of map app use, we also conducted an analysis of individual map usage patterns. It is important to note that no two individuals are identical. To limit the scope of this analysis, we restricted our comparison to two individuals. The selection was made on the basis of the differing tap speeds prior to data alignment with a similar study period length.

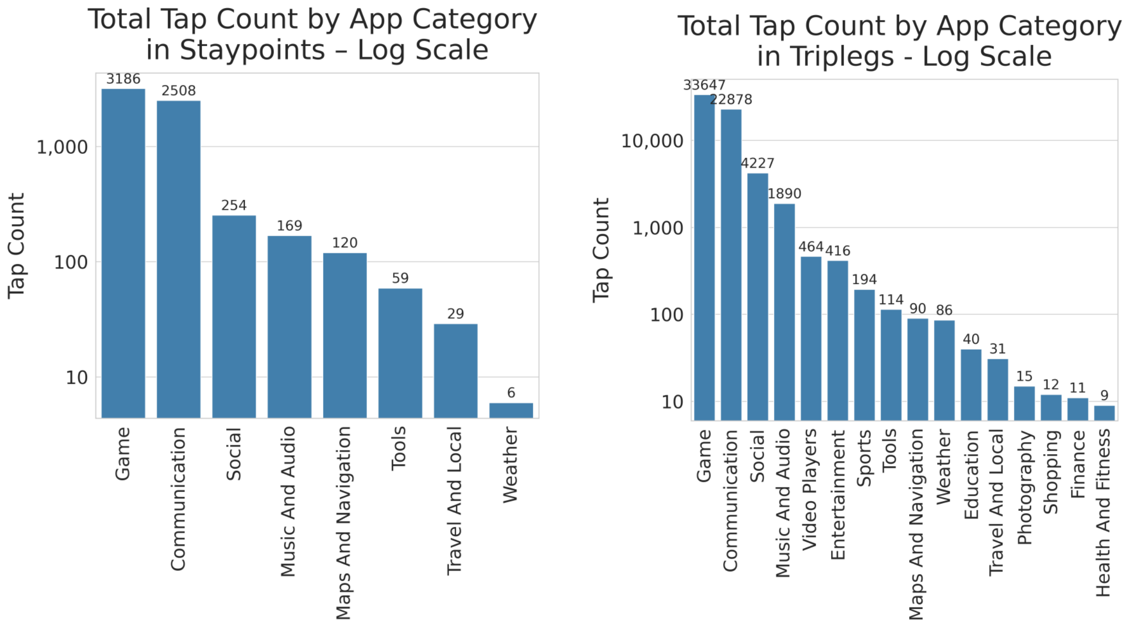
This section presents findings on general app usage, map app usage, and map app usage supplemented with location-based contextual data. For general app usage, we report the number of taps in various app categories distinguished by mobility state. For map app usage, we provide the tap counts in map applications by mobility state, along with the session metrics for both states of mobility. Concerning context-enriched map app usage, session metrics were visualized based on categorization by purpose, OSM classified tags, and motorization speed.

4.4.1 User 20: Long Session Durations and Low Tap Speed

The duration of the study for user 20 was 27 days. Before data alignment, the participant had a median app session duration of 44 s (log transformed: 3.78) and a tap speed of 0.72 taps/s (log transformed 0.63). As for distances traveled, user 20 was based in Switzerland, but took two long-distance trips to northern Italy.

4.4.1.1 General App Use

The total tap count per app category showed an exponential relationship, but was more skewed for staypoints than triplegs, since the top two categories in staypoints had a visible higher tap count *Figure 25*. The top three categories with the highest tap frequency were games, communication, and social apps. Of the map categories, maps and navigation had a higher tap count than travel and local in both states of mobility. In the travel and local category, the total tap count was very similar in stationary and non-stationary movement. For maps and navigation, the tap count was higher in the stationary than non-stationary state, even though in total there were more taps in triplegs. Thus, proportionally, map apps had more taps in staypoints than triplegs.



(a) Staypoints *(b) Triplegs*

Figure 25: User 20: Barplots of Tap Counts by State of Mobility

4.4.1.2 Map Use

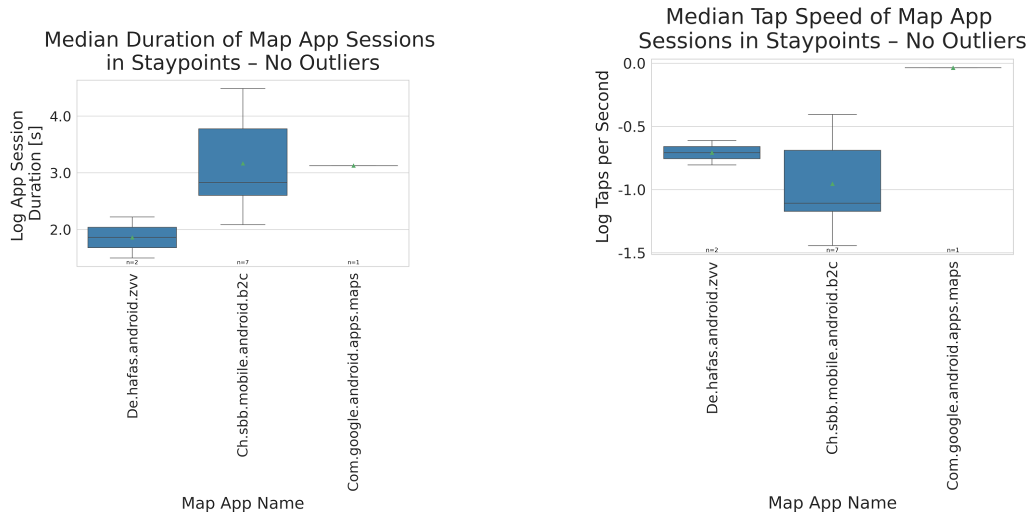
Three different map apps were accessed by user 20: SBB Mobile, ZVV-Timetable and Google Maps. In both states of mobility, SBB Mobile had the highest tap count. The information app ZVV-Timetable showed much more usage during stationary periods, whereas Google Maps was only accessed in the non-stationary state.

Table 5: User 20: Map Tap Count in Triplegs by App Name

App Name	TPLS Map Taps	SP Map Taps	Total Map Tap Count
ch.sbb.mobile.android.b2c	90	120	210
de.hafas.android.zvv	31	7	38
com.google.android.apps.maps	-	22	22

Staypoints

In stationary periods, ZVV-Timetable recorded the lowest session durations at 1.85, while SBB Mobile and Google Maps had longer session durations around 2.83 and 3.13, respectively (*Figure 26 a*). Regarding the tap frequency, interestingly, Google Maps had the highest tap speed near 0 (-0.04), in the middle is ZVV-Timetable at -0.71 and SBB Mobile with the slowest tap speed at -1.11 (*Figure 26 b*). A Kruskal-Wallis test for both metrics returned a $p - value > 0.05$, so statistically the median differences between map apps were not significant.

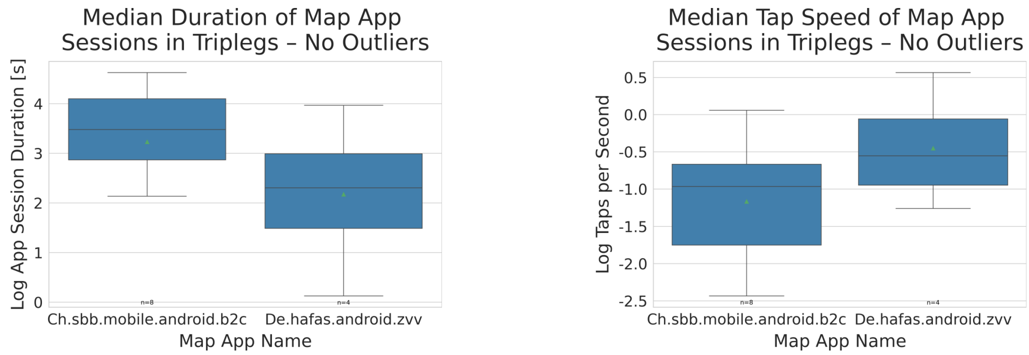


(a) *Median Duration (Log Scale)* (b) *Median Tap Speed (Log Scale)*

Figure 26: User 20: Boxplots of Median Map Session Metrics in Staypoints

Triplegs

During movement, the app sessions were longer than while stationary. The median app session length in ZVV-Timetable (2.30) was shorter than SBB Mobile (3.48) (*Figure 27a*). The tap speed was lower in ZVV-Timetable (-0.55) than SBB Mobile (-0.96), indicating that an increase in session duration did not lead to an increase in taps (*Figure 27b*). To statistically check whether the differences were significant, a Kruskal-Wallis test was employed. With a $p-value > 0.05$ we failed to reject the null hypothesis.

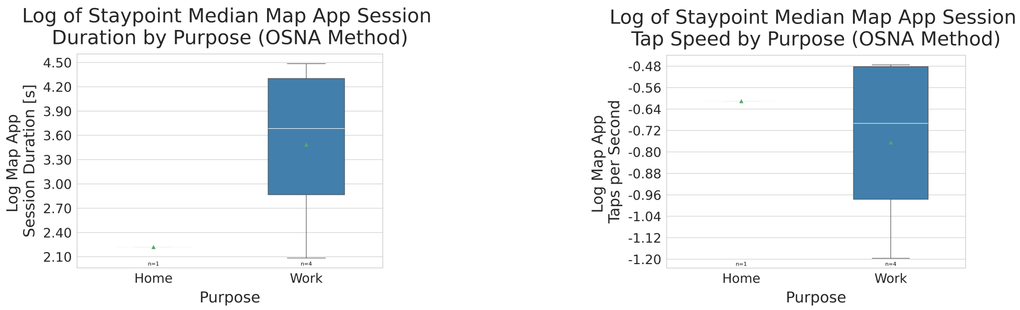


(a) *Median Duration (Log Scale)* (b) *Median Tap Speed (Log Scale)*

Figure 27: User 20: Boxplots of Median Map Session Metrics in Triplegs

4.4.1.3 Map Use with Context

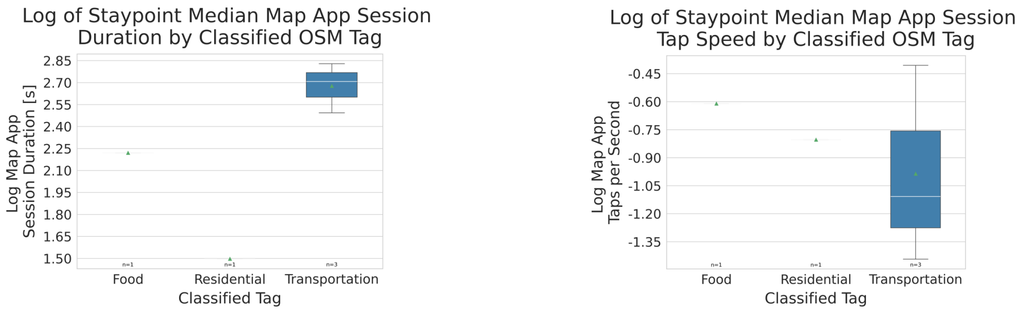
Of the 41 staypoints throughout the study period, 17 were assigned a purpose and in five of these, map use was recorded. Four of the staypoints assigned a purpose with map use were at work, while only one was used at home. *Figure 28* illustrates the boxplots for the map app session metrics of staypoints, classified according to the OSNA method. The duration of the home session was shorter (2.22) than that of the



(a) Median Duration (Log Scale) *(b) Median Tap Speed (Log Scale)*

Figure 28: User 20: Boxplots of Median Map Session Metrics by Purpose (OSNA)

median map session at work (3.68). With regard to tap speed, the value observed at home (-0.61) was higher than at work (-0.69). Furthermore, a smaller IQR was observed for tap speed (0.49) compared to duration (1.44) at work locations. A Kruskal-Wallis test did not yield statistically significant differences in medians for map use behavior (duration or tap speed).



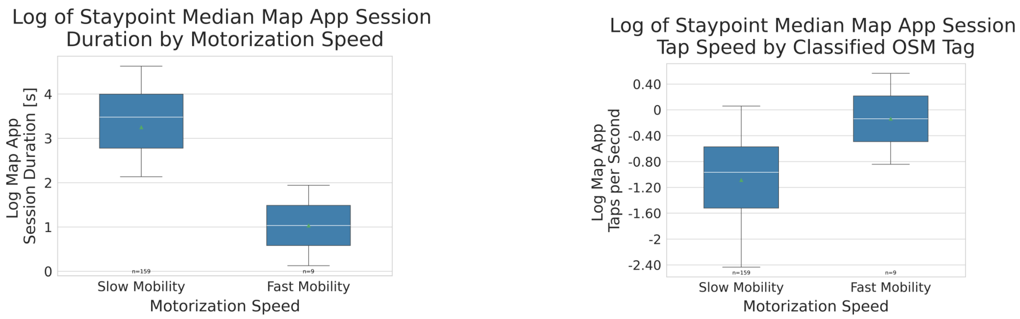
(a) Median Duration (Log Scale) *(b) Median Tap Speed (Log Scale)*

Figure 29: User 20: Boxplots of Median Map Session Metrics by POI Classified Tag

With the OSM method, five staypoints were also identified with map use and assigned to a POI classification. Three belonged to places of transport, one to food, and one to a residential area. The session durations vary quite a bit, shortest in residential places (1.50), slightly longer for food (2.22) and longest in transportation (2.71)(*Figure 29a*). Interestingly, the tap speed was highest for food (-0.61) although it did not have the longest session durations (*Figure 29b*). The tap speed in residential areas was in the middle (0.80) and the lowest in places of transportation (-1.11). The Kruskal-Wallis test here also failed to reject the null hypothesis ($p > 0.05$).

Triplegs

Of a total of 168 triplegs, 12 were identified as having accessed maps. Most of these instances exhibited slow mobility characteristics (10). The duration of the sessions was markedly longer in the slow mobility segments (3.48) than in fast mobility (1.03) (*Figure 30a*). The frequency of taps was observed to be lower in slow mobility (-0.96) than in fast mobility (-0.14). The Kruskal-Wallis test produced a p-value of 0.053, marginally above the threshold to reject the null hypothesis regarding session duration and motorization speed. For the tap speed, the p-value was even higher, so the null hypothesis was also not rejected.



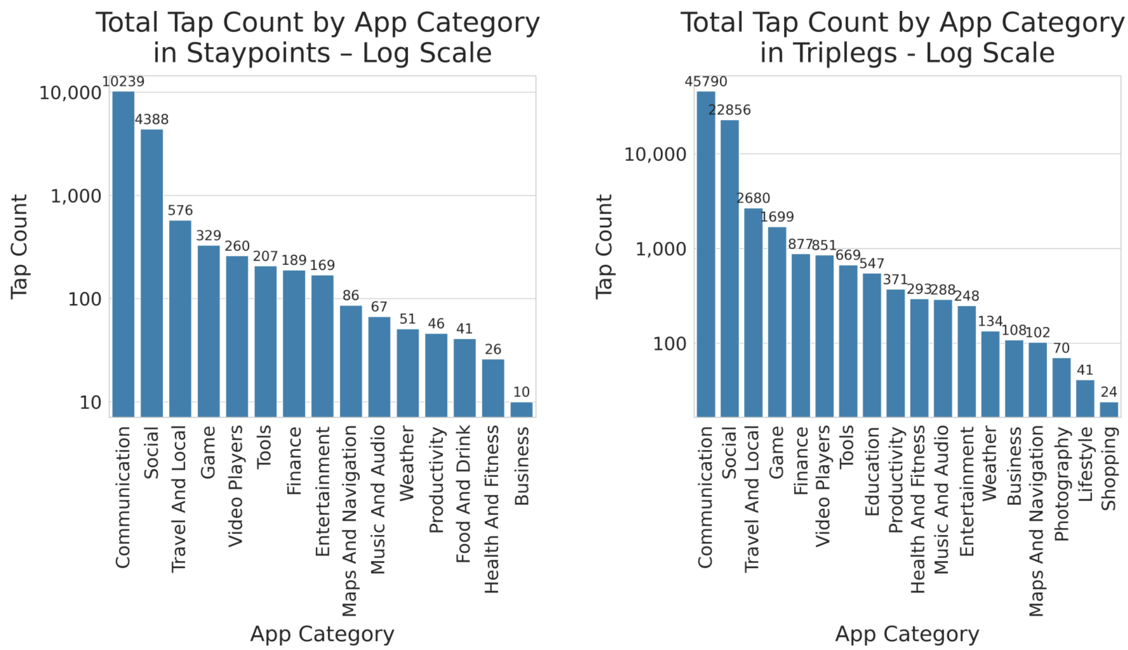
(a) Median Duration (Log Scale) *(b) Median Tap Speed (Log Scale)*

Figure 30: User 20: Boxplots of Median Map Session Metrics by Motorization Speed

4.4.2 User 15: Short Session Durations and High Tap Speed

Next, we present findings for a participant who exhibited short session durations and increased tap speed prior to GPS and tap alignment. User 15 participated for a study period of 23 days, with a median app session duration of 22 seconds (log transformed 3.09) and a tap speed averaging 1.88 taps/second (log transformed -0.33). This participant was located in Switzerland and made two long-distance trips to other countries, specifically France and Greece.

4.4.2.1 General App Use



(a) Staypoints *(b) Triplegs*

Figure 31: User 15: Barplots of Tap Counts by State of Mobility

The barplots displaying cumulative tap counts in staypoints and triplegs demonstrated that the three most popular app categories were communication, social, and travel and local apps, irrespective of the mobility state (*Figure 31*). Moreover, the barplots are rather skewed, even on a logarithmic scale, with the top two app categories possessing much higher tap counts than the rest. Map apps within the travel and local category exhibited a substantially higher cumulative tap count than apps in the maps and navigation category.

4.4.2.2 Map Use

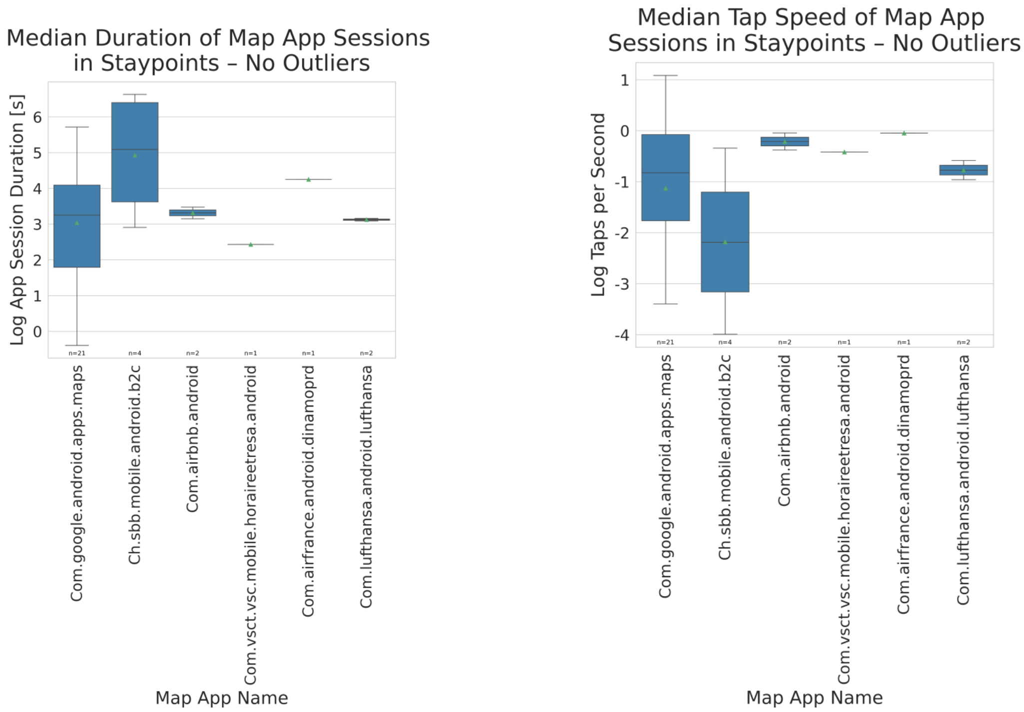
A total of 29 out of 72 staypoints resulted in the usage of map applications. Google Maps was the application with the highest cumulative tap count, irrespective of the mobility state. In staypoints, the airline app Lufthansa and the ticket shop app SBB Mobile were among the other frequently used applications. Conversely, the second and third-highest tap counts in triplegs was recorded in Airbnb and the ticket shop app SNCF Connect ('com.vsct.vsc.mobile.horaireetresa.android'). It was notable that this user had accessed three different airline apps (Lufthansa, AirFrance, and Aegean Airlines) during the study period.

Table 6: User 15: Map Tap Count in Triplegs by App Name

App Name	TPLS Map Taps	SP Map Taps	Total Map Tap Count
com.google.android.apps.maps	2464	511	2975
com.airbnb.android	461	47	508
com.vsct.vsc.mobile.horaireetresa.android	364	18	382
com.lufthansa.android.lufthansa	74	121	195
ch.sbb.mobile.android.b2c	102	86	188
com.riliclabs.countriesbeen	149	-	149
com.airfrance.android.dinamoprd	-	78	78
com.aegean.android	6	-	6

Staypoints

Taking a closer look at the session duration of map apps in staypoints, values ranged from 2.43 (SNCF Connect) to 5.09 (SBB Mobile). Google Maps, Airbnb, and Lufthansa were around 3.2 (*Figure 32a*). The tap speed ranged from -0.05 (AirFrance) to -2.19 (SBB Mobile). Google Maps had a median tap speed of -0.83, and all other apps except SBB Mobile had a faster tap speed (*Figure 32b*).

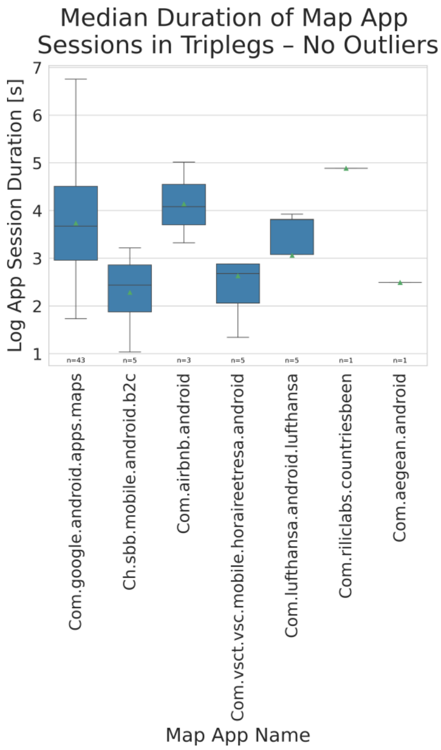


(a) Median Duration (Log Scale) *(b) Median Tap Speed (Log Scale)*

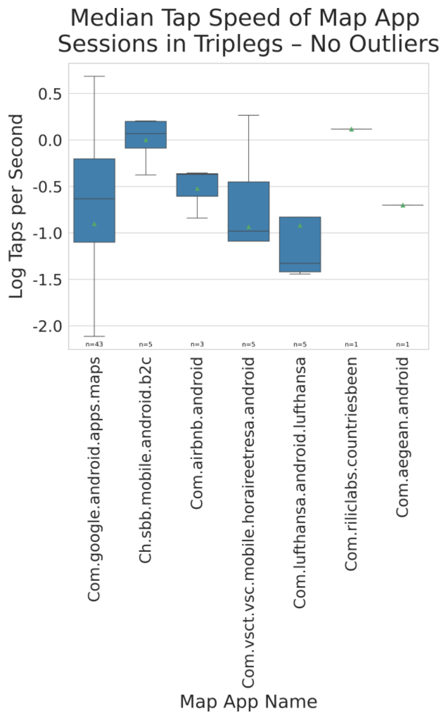
Figure 32: User 15: Boxplots of Median Map Session Metrics in Staypoints

Triplegs

Next, we present the results for the map session metrics in triplegs. In terms of session duration, there was considerable variability between the different apps (*Figure 33 a*). The two ticket shop apps SBB Mobile and SNCF Connect, as well as Aegean Airlines, had the shortest session durations of approximately 2.5. In contrast, the longest session durations were observed in the Countries Been application, with a median duration of 4.89 and Airbnb also with a value exceeding 4. Google Maps (3.68) and Lufthansa (3.81) fell within the mid-range of tap speed. With respect to the tap speed, the values ranged from -1.33 (Lufthansa) to 0.12 (Countries Been) (*Figure 33 b*). Google Maps exhibited a tap speed of -0.63, while SBB Mobile demonstrated a higher value of 0.07. The Kruskal-Wallis test produced a p-value of 0.04 for the duration of the session, which led to the rejection of the null hypothesis. Conversely, the p-value of 0.24 for tap speed did not meet the significance threshold for rejection.



(a) Median Duration (Log Scale)



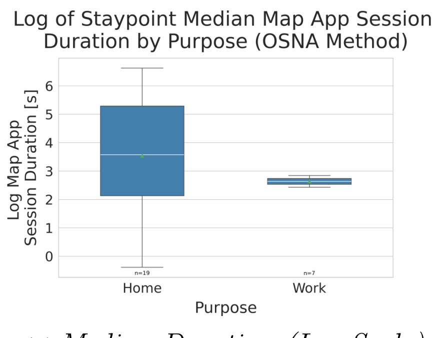
(b) Median Tap Speed (Log Scale)

Figure 33: User 15: Boxplots of Median Map Session Metrics in Triplegs

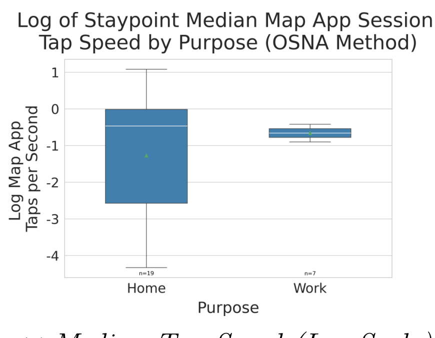
4.4.2.3 Map Use with Context

Staypoints

For user 15, a total of 12 staypoints with map app usage were identified and assigned a purpose (out of 101 staypoints and 26 staypoints with a purpose). The sessions were longer at home (3.57) than at work (2.64). The tap speed was slightly higher at home (-0.47) than at work (-0.66). However, the Kruskal-Wallis test did not indicate significant differences ($p - value > 0.05$).



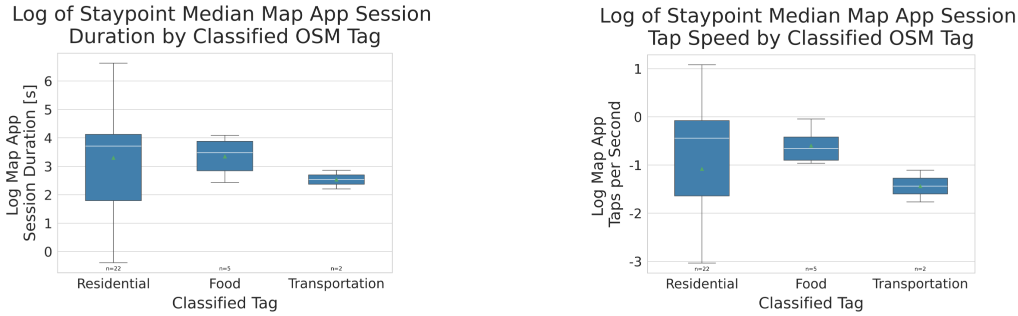
(a) Median Duration (Log Scale)



(b) Median Tap Speed (Log Scale)

Figure 34: User 15: Boxplots of Median Map Session Metrics by Purpose (OSNA)

A total of 29 staypoints were context-enriched with a POI tag and included map use. The duration of the sessions was found to be the longest in residential areas (3.71), intermediate in food-related locations (3.48), and shortest in transportation-related areas (2.54). The range was highest in residential areas, which also exhibited the highest number of staypoints in this category (22 vs. 5 and 2) (*Figure 35 a*). The lowest median tap speed was recorded at places of transportation (-1.43), while areas of food (-0.66) and residential (-0.44) exhibited slightly higher values (*Figure 35 b*). These differences were statistically insignificant for both duration and tap speed, as indicated by the Kruskal-Wallis tests with p-values greater than 0.05.

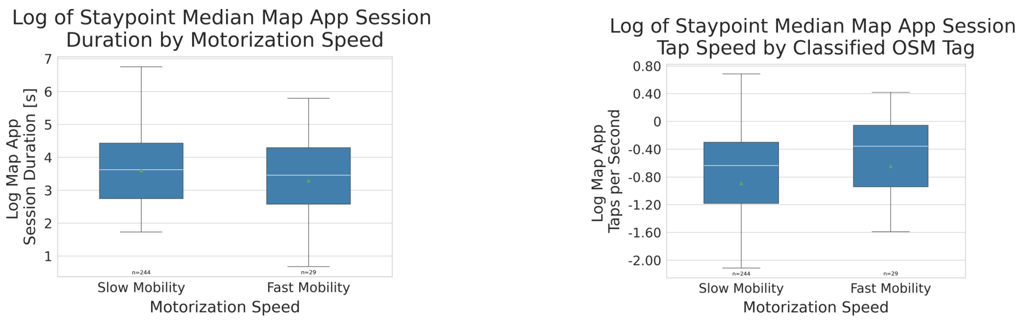


(a) Median Duration (Log Scale) *(b) Median Tap Speed (Log Scale)*

Figure 35: User 15: Boxplots of Median Map Session Metrics by POI Classified Tag

Triplegs

For user 15, a total of 56 triplegs involved map usage. The median session duration was slightly longer during slow mobility (3.62) than during fast mobility (3.46), with a similar IQR (1.68 and 1.71) (*Figure 36 a*). It was observed that the minimum (within 1.5 IQR of the lower quartile) and maximum (within 1.5 IQR of the upper quartile) of the boxplot were approximately 1 unit higher for slow mobility compared to fast mobility. The differences in tap speed were somewhat more pronounced. During slow mobility, user 15 had a median of -0.64, which was slightly lower than the median of -0.36 during fast mobility. The IQR was nearly identical at 0.88, but the minimum and maximum values within 1.5 IQR of the first and third quartiles were more extreme in slow mobility. Although minor variations were detected in the boxplots, the Kruskal-Wallis test produced p-values exceeding 0.05 for both metrics. Thus, we failed to reject the null hypotheses.



(a) Median Duration (Log Scale) *(b) Median Tap Speed (Log Scale)*

Figure 36: User 15: Boxplots of Median Map Session Metrics by Motorization Speed

5 Discussion

The objective of this discussion is to synthesize and interpret the findings on the usage patterns of map apps in the context of user mobility presented in chapter 4. The analysis distinguished between stationary and non-stationary states of mobility and investigated the impact of context-enriched factors, including purpose, points of interest (POI), and motorization speeds on mobile map app usage. This chapter addresses the observed differences between stationary and non-stationary behaviors, the role of context in enriching the understanding of these patterns, and how individual variations in map usage emerge are discussed. Furthermore, the constraints of the data and methodologies are addressed. This discussion also highlights the broader implications for mobile app design and future research of mobility and app usage.

Before presenting the findings, it is essential to note that they pertain specifically to mobile applications on smartphones and tablets. Thus, the results cannot be generalized to the use of the underlying services (Böhmer et al., 2011). For example, if a map service was utilized at home on a computer, the data was not collected. Similarly, if the map service was accessed via an internet browser app, it was also not be recognized as map use.

5.1 Macro-Level Map App Usage: Stationary vs. Non-Stationary Behavior

The first inquiry sought to identify and analyze macro-level tapping and usage patterns in mobile map applications, differentiating between stationary and non-stationary states of user mobility.

There was more data for non-stationary movement than stationary, based on the average time spent per day but also in total time spent. This differs from existing literature that takes into account phone usage and the states of mobility like Verkasalo (2009), and the intra-session data from Trestian et al. (2009). While the time spent on phones was higher than in previous studies, the values are closer with the average inter-session move and stationary times (where no phone was used) from Trestian et al. (2009) at 8 hours and 23 minutes, and 4 hours and 25 minutes, respectively. This increase in phone use likely reflects the shift in society, where phones are becoming more present and a part of daily life (Trott et al., 2022).

Delving into map use, we noted an increased use of maps in stationary than non-stationary state of mobility, with one-third of staypoints recording map use and one-fifth of triplegs. Additionally, the cumulative tap counts by map app name also showed that there was an exponential relationship (straight line in the log-scaled barplots), regardless of the state of mobility. Google Maps and SBB Mobile were the two most popular map apps by far, with the most number of accesses from staypoints and triplegs, and the highest tap count.

Regarding the map metric session duration, it was observed that map application sessions were generally longer when users were non-stationary as opposed to stationary. For instance, the two most frequently used apps, Google Maps, demonstrated session times of 3.18 for stationary phases compared to 3.73 for non-stationary periods. Similarly, SBB Mobile had session durations of 2.89 and 3.24 for stationary and non-stationary phases, respectively. Interestingly, all map apps with at least five data points for both mobility states were longer in the stationary state, except Tripadvisor and Flightradar24. Staypoint sessions were also longer for AirFrance (SP n=4, TPLS n=10) than tripleg sessions. The data had a limited dataset for map apps with a flight and travel plan purpose, so further research would be needed to check if the longer staypoint than tripleg durations indicated a different kind of map use for such apps.

The longer duration of map sessions in triplegs suggested an increased cognitive load when moving in the environment, which requires users to spend more time in the app (Griffin et al., 2024). It also raises the question of how mobile map design could pose potential safety concerns to the user when attention is divided between the application and the environment. For example, in the context of the development and design of navigation map apps, this could apply to apps that inform users about traffic zones, report accidents, speed limits while driving, or select the safest route when planning (instead of duration) (e.g., Kusumasari et al. (2022)).

An intriguing question arises regarding potential differences in app usage duration between tourists and locals. Some evidence indicated that apps utilized in foreign countries, such as Carris (3.92) and Orario Treni (3.29), demonstrated prolonged usage while stationary. They had 7 and 8 data points, respectively. Insufficient data was available for other ticket shop apps, including DB Navigator, Trenord, and

Trainline, as they had fewer than five data points for stationary usage, thereby limiting the informative value of the data. The trend was less clear in non-stationary movement, where ADO Boletos, Flixbus, Orario Treni, and Trenord had higher median session durations than SBB Mobile. Four apps exhibited shorter sessions: MVG Fahrinfo München, SNCF Connect, Trainline, and Trenitalia. Trenitalia is worthy of further investigation as it exhibited a markedly lower value (2.71) and ranked third in terms of data source, with a total of 55 triplegs, after SBB Mobile and Fairtiq. The post-hoc Dunn's test revealed a statistically significant difference to OsmAnd+. It would be beneficial to conduct further research to determine the number of individuals who accessed the app and whether similar trips were taken. This could indicate whether they used the app more frequently, indicating that they use it more as a local than a tourist, which would explain the shorter duration. Furthermore, it was notable that navigation apps such as swisstopo and offline apps, including OsmAnd+, MAPS.ME, exhibited slightly longer durations than Google Maps, both in stationary and non-stationary states of mobility. This may be indicative of users of these apps spending more time exploring the map. In addition, the utilization of offline navigation maps could be indicative of the apps used by tourists, as they lack access to mobile data or need to save battery.

Very interesting was Fairtiq, which reflected a unique map use pattern. The median session duration was much lower than other map apps, with values of 0.86 and 1.29 for staypoints and triplegs, respectively. This can be explained by the way that Fairtiq works, namely, it only required users to start and stop the trip (check-in and check-out). The app then automatically computed and selected the least expensive ticket for the traveled route throughout the day, removing the step of the user having to plan or pick the correct ticket and knowing the name of the stations.

Similarly to the duration, the tap speed of Fairtiq was notably slower than that of other map apps. The straightforward nature of the process, which merely requires a simple swipe to check in and out, is likely the reason behind this outcome. In terms of mobility states, map app sessions exhibited a marginally higher frequency in stationary scenarios compared to non-stationary ones. Overall, the variability in tap speeds was notably lower than for durations, signifying a more consistent range for tapping frequency across different map applications. We also recognize that the level of aggregation of the tap speeds by the state of mobility and per app was too high to reflect the differences between different map activities, including exploration, search, and route planning, or following navigation directions (Kiefer et al., 2017). These activities may differ in tap speeds, but would not be reflected at this level of analysis (tap speed per session).

For map apps, there were some significant differences in the median tap speed, according to the post-hoc Dunn's test. In general, the tap speed of (offline) navigation apps was higher than that of the ticket-shop apps. Google Maps exhibited a tap speed of -0.35, which was more than twice the speed of SBB Mobile's tap speed of -0.81 when comparing their logarithmic values. Note that when the logarithm is reversed, the actual difference in tap speeds is slightly less pronounced.

It was also interesting that the number of apps with significantly different medians was limited to a few apps, like Google Maps, SBB Mobile, Publibike, OsmAnd+ and Fairtiq. However, a closer look at the number of times accessed from staypoint or tripleg showed that these apps were frequented the most. Since map apps only make up such a small part of phone use in general (Reichenbacher et al., 2022), a larger-scale study could reveal more indicative patterns.

We also explored the temporal aspect of map app access by time of day and day of the week. In this regard, existing research with tappigraphy visualized map use in regard to map taps (Reichenbacher et al., 2022). They mentioned a day-night pattern, which was also reflected in our data. However, they found the highest use in the afternoon until the early evening (13:00-19:00) of the second half of the week (Thursday to Sunday). The two peaks were spotted around lunch (13:00) and before dinner (18:00). Our findings differed slightly, but we considered the time an app was accessed, and not the tap count. For stationary movement, maps were accessed steadily in the morning from 5:00 until the early afternoon. Similarly to Reichenbacher et al. (2022), the highest map use was recorded in the afternoon, but cut off slightly earlier at 17:00. We found three local peaks, two in the morning at 6:00 and 10:00, and the largest one in the middle of the afternoon at 15:00. Throughout the week, we found the highest map use on Mondays and Thursdays, which decreased over the weekend (Friday to Sunday). For the non-stationary data, we saw four peaks throughout the day, a small one in the morning (7:00), then before lunch (11:00), in the middle of the day (15:00), and before dinner (18:00). We see more similarity to the existing literature with the days of the week, with Thursdays to Saturdays having the highest number of maps accessed. Interestingly, non-stationary map use was lowest on Sundays, with local peaks on Mondays and Fridays.

In addition to observing when the map apps were accessed the most, we also visualized which map apps were accessed. App-specific variations were consistent across both datasets, such as SBB Mobile being accessed more frequently than Google Maps during early morning hours. Google Apps was accessed more in the afternoon, with a peak around 2pm. This differed slightly from Böhmer et al. (2011), who found a strong peak in the early evening hours, though they also mentioned a higher use in the afternoon. Fairtiq showed peak usage in the very early morning before work (SP: 5:00, TPLS: 5:00–7:00) which could indicate usage during the commute in the morning. However, it is unclear why this is not matched in the evening for the evening commute, and is instead accessed more often in the early afternoon. The access of the bike rental app Publibike started slightly earlier while stationary, at 6:00, and an hour later in triplegs. In both states of mobility, it was accessed much more frequently in the later afternoon, with a peak at 15:00, and steady use until dinner time (18:00). Additionally, the stationary data highlighted the use of travel booking apps like Booking and Airbnb, which were mainly accessed in the evening, a detail less noticeable in the non-stationary data. There was also some weekend-specific behavior in the stationary dataset, such as the increased usage of the Actionbound game on Saturdays and Uber's peak on Fridays and Saturdays, which were not as pronounced in the triplegs data.

In this thesis, the apps which were used before or after a session were not taken into account. However, we looked at the specific example of AirFrance, which had exceptionally high session duration, with only four sessions of which one was extremely long (20 minutes) (*Figure 8*). It was noted that the very long session was followed by a relatively short session. This could indicate a possible relation between temporally close sessions. For example, for AirFrance, a user could have spent a considerable amount browsing and comparing flights and booking a flight. Soon after, the user returned to the app to quickly check something about the newly booked trip. We conclude that possible directions for future research include the study of temporally close sessions of the same app to better understand how a specific application is used, or the study of apps that precede and follow an app session (see (Böhmer et al., 2011)).

5.2 Macro-Level Map Usage with Context Enrichment: Impact of Purpose, POIs, and Modes of Transport

The second research question aimed to investigate whether distinct map usage behaviors could be discerned through context enrichment of stationary locations (purpose and POIs) and categorization of non-stationary travel by transport modes (fast vs. slow mobility). We will first compare the two context enrichment methods employed for stationary data and how they compare with the existing literature. In a second step, we discuss the findings of the categorization for non-stationary data.

5.2.1 Stationary Movement with Purpose and POIs

The first thing to take into account with both staypoint classification methods is that not all staypoints were classified. With the OSNA method, only a third of all staypoints were enriched with context. We then further restricted the analysis to staypoints that included map use, which was also about a third of the classified app or approximately 10% of the stationary data. We also noticed that the OSNA method was not able to find the context for every individual, especially the home category. This differs from the frequency method, which is bound to find context for all participants as long as the users visited at least two locations. The OSM method classified more than double the staypoints at 85.10%. For the enriched map use data, it is 29% of all stationary data. The trade-off between the purpose and POI classification is the loss of data for purpose method because fewer social contexts are considered (finer-grained classes with POIs tags than purpose), but it is computationally more efficient. Future research could integrate these methods to determine work and residential locations, followed by computing the OSM tag for classifying the remaining data. Thus, the system could autonomously distinguish between the user's own home and other residences, such as those of family or friends, akin to the differentiation made in the study by Do et al. (2011) regarding home and friend-home, but without necessitating the user to manually label the locations.

Examining the relative proportion of staypoints with map use visualized in Marimekko charts, the purpose classification did not indicate different map use at home (33.65%) and work (31.93) locations, as visualized in the Marimekko chart in *Figure 15* or the χ^2 independence test. In contrast, the POI classification found a relationship between the classified POI categories (residential, transportation, food, commercial, education, tourism, entertainment, and healthcare) and the access of map apps (*Figure 20*). Upon statistical inspection with the adjusted pairwise χ^2 test of independence, the only statistically significant relationship was found between residential and food locations. The Bonferroni correction, which is known to be conservative, adjusts the significance threshold to account for multiple comparisons, reducing the risk of false positives (VanderWeele and Mathur, 2019). However, it may increase the likelihood of Type II errors (false negatives), potentially overlooking some real associations.

Surprisingly, map apps were not accessed much more often in places of transportation than any other place. In fact, it was very similar to residential areas and tourist attractions (*Figure 20*). However, map use is still higher than in places of commerce, education, and dining, which is understandable. People were more likely to use map apps to plan a trip or explore an area while at home, in tourist areas (e.g., if they had not been there before), or in a place of transport (e.g., waiting for public transport at a train station or bus stop) than at work, eating out, or studying. Previous research had demonstrated a correlation between the distance traveled by participants and their use of maps (Yang et al., 2016; Zingaro and Reichenbacher, 2022). A distinct 'home' and 'travel' map use behavior was found by Zingaro and Reichenbacher (2022), where they considered the distance away from home. With our method, we could supplement the statement that people access map apps less often in places of food than at home. On the other hand, we were unable to statistically find that map use was higher in places of transport than other functional places (cf. (Yang et al., 2016)). From the Marimekko plot, we visually observed that the proportion of staypoints with map access was higher in transportation hubs than in commercial areas, educational institutions or food locations. However, it should be noted that in their study, Yang et al. (2016) only considered places of transportation, educational institutions, work, and entertainment but not home or residential areas, as they were limited to phone traffic with mobile data.

Regarding map session metrics, no statistical differences were found between usage at home and at work (*Figure 16*). This could indicate that only differentiating between home and work locations is not fine-grained enough to discern the 'home' and 'travel' map use behavior was found by Zingaro and Reichenbacher (2022). Other potential reasons for similar map usage behavior at home and work locations might be the rising trend of remote work, which blends non-work and work activities on smartphones (Das Swain et al., 2022), an individual's unemployment or work in the evening or on the weekends. With the OSM classification, the Kruskal-Wallis test found a difference between the OSM groups and median session duration. Though a post-hoc Dunn's test did not reveal which categories had different median durations, areas of entertainment and tourism did show a tendency for longer session durations than the rest of the categories. As for tap speed, it was also noted that the variability was much higher for entertainment and tourism, with a slightly lower median compared to the rest of the categories. However, statistically, we only found that the tap speed between commercial and touristic areas was different. A possible reason for the lower tap speed in tourist areas could be that people spent more time studying the map visually than exploring it through haptic interactions.

Very interesting were the findings on which apps had the most taps, depending on the context of the staypoint. With purpose distinction, we observed a greater use of travel booking apps and flight apps at home, while at work, navigation apps were more prominent (*Figure 17*). Google Maps, SBB Mobile and Publibike had a relatively high proportion in both places. For the three most common POI classification (residential, transportation, and food), we found that Google Maps was the most used app. Similarly to the home category, SBB Mobile and Publibike were the second and third most used apps in residential areas. While booking and flight apps were accessed in residential areas, they were much less used than in the home category. We did observe the presence of the navigation apps OsmAnd+ and swisstopo which were not present at the OSNA home staypoints. In transportation places, ticket shop apps were more present, which makes sense as people needed to buy tickets before using public transportation vehicles. The food staypoints showed a slightly different map use behavior. Vehicle reservation apps were more present, indicating that travel to and from restaurants was likely less with public transport than short-distance vehicles like scooters and bikes. Surprisingly, SBB Mobile was not the second most used app, instead, the booking apps Tripadvisor and Booking, held the second and third place, respectively.

Future work could combine the study of contextual information about stationary periods with the distances traveled by individuals. The existing literature has indicated that there is a relationship between map use and distance traveled (Yang et al., 2016; Zingaro and Reichenbacher, 2022). As an exploratory work, this thesis presented a significant contribution by demonstrating an automatic classification of locations that could be expanded to numerous categories, in contrast to the manual classification of places employed by Yang et al. (2016); Do et al. (2011). Furthermore, the study revealed that map apps with distinct primary purposes could be differentiated based on the location-based context of the use of mobile devices. In a next step, we discuss the findings of map use in the context enrichment non-stationary mobility.

5.2.2 Non-Stationary Movement with Mode of Transportation

Unlike stationary data classification methods, all triplegs were classified with a motorization speed to approximate the modes of transportation. The majority of non-stationary data was classified as slow mobility, indicating more local travel than long-distance trips. This is understandable, as most of the individuals were based in a larger Swiss city. Travel in urban areas is often easier with slower modes of transport than driving (e.g., traffic, limited and expensive parking spaces). In terms of relative map use, maps were twice more likely to be used in fast mobility than slow mobility (*Figure 22*). Given the increased number of slow mobility triplegs, it was not surprising that a greater variety of map applications were used during periods of slow mobility compared to fast mobility (*Figure 23*). In both situations, Google Maps and SBB Mobile were the two most frequently utilized apps. Additionally, there was a higher number of booking apps and total number of touchscreen interactions in map apps in the slow mobility context. While at first it may be surprising that booking apps where used while non-stationary, a more detailed look into some apps indicated that they function is not only limited to booking hotels, cars or flights. For example, Tripadvisor contains restaurant recommendations, while Booking.com has suggestions for attractions. It was also no surprise that Zoo Zürich, an app with information about the zoo, was only accessed during slow mobility, since fast mobility transport modes cannot be used in the zoo.

The analysis of map use behavior also indicated interesting results (*Figure 23*). During slow mobility, a significant increase in time spent interacting with map applications was observed compared to during fast movement. However, the frequency of user interactions (tap speed) remained consistent across both slow and fast travel modes. This disparity in usage duration without a corresponding change in interaction frequency could suggest potential differences in navigation complexity or environmental engagement based on travel speed. Slow modes of travel, such as walking, may have necessitated more frequent reference to map applications, be it for guidance while navigating or to book travel plans in the booking apps. Extended map usage during slow travel might have indicated heightened user engagement with the surrounding environment, manifesting itself as exploratory behavior or multitasking. The consistency of the tap speed across the travel modes suggested that the underlying interaction paradigm remained constant, possibly due to the consistent interface design or the user adopting a uniform interaction rhythm to manage the cognitive load. These observations highlight the need for further research to elucidate the cognitive processes and user motivations underlying these patterns, potentially forming the design of more context-aware navigation systems.

5.3 Micro-Level Map App Usage Patterns: The Role of Mobility and Context

The final area of investigation focused on comparing tapping and usage patterns within map applications at the micro-level, considering both the user's state of mobility and the context-enriched mobility state.

A comparison was conducted between two users with distinct general app usage behaviors: user 20, who exhibited longer session durations and a lower tap speed prior to data alignment, and user 15, who had shorter sessions and a higher tap speed. Notably, user 20 preferred apps in the maps and navigation category (*Figure 25*), whereas user 15 had higher tap counts in the travel and local category

(*Figure 31*), regardless of whether they were stationary or in motion. Both users accessed SBB Mobile and Google Maps, yet their engagement differed: user 15 only accessed Google maps while Stationary, and preferred SBB Mobile.

Upon comparing stationary map session metrics, an interesting reversal was observed in session durations relative to their overall app behavior. Despite user 20 typically having longer general session durations, their map session durations were shorter than those of user 15, especially for SBB Mobile (5.09 for user 15, 2.8 for user 20). However, the tapping speed did not show a clear difference between the users. For both users, SBB Mobile had the lowest tap speed, but it was slower for user 20 (-1.11) than for user 15 (-2.19). In contrast, Google Maps exhibited a higher tap speed in user 15 (-0.83) compared to user 20 (-0.04). If we compared the individuals' results to their general session metrics before the alignment (taking the natural logarithm), we noticed that the session durations were shorter and tap speeds lower for all map apps in user 20. For user 15, map sessions were longer than the average app session, except for SNCF Connect, the ticketing app in France. This divergence between general app metrics and map app behavior suggests that general app session metrics cannot fully predict map app usage, pointing to the specialized nature of map interactions.

When considering map usage during triplegs, the differences between the two participants became less distinct than in the general session metrics before alignment. User 15 exhibited longer map sessions than user 20, which was consistent with their stationary behavior. Upon examining the duration of the map sessions in relation to their overall session length, the analysis revealed that the median duration of map sessions for user 20 was shorter than their average session duration.(*Figure 27*). In contrast, user 15 did not show a definitive trend, with roughly half of the apps showing longer sessions and the other half shorter compared to their average app session before alignment (*Figure 33*). The tap speed during triplegs did not show marked differences between the users, with both generally exhibiting lower speeds during map app use compared to general app sessions. While for user 20 all apps had slower speeds than the general tap speed, user 15 had two exceptions with SBB Mobile and Countries Been.

These findings revealed that individual behavior in map app usage remained relatively consistent regardless of the state of mobility. Moreover, an individual's average tap speed and session length across all apps did not necessarily imply similar patterns of map app usage. User 15, despite having longer map sessions, did not show a proportionate decrease in tap speed, further underscoring that session length does not necessarily directly correspond to interaction intensity.

In the final part of the analysis, the map session metrics were contextualized using staypoint and tripleg data. Fewer staypoints were identified for user 20 than for user 15, both with and without context. User 20's map sessions were shorter at home than at work, while user 15 displayed the opposite pattern. Additionally, user 20's median session durations were more extreme compared to user 15. Both users exhibited faster tap speeds at home than at work, though the differences between categories were not statistically significant, aligning with the results of the macro-analysis.

The OSM method revealed that both participants only accessed map apps in residential, dining, or transportation areas. The median map session duration in places of transportation was longer for user 20 than user 15. The food and residential areas for user 20 included only one staypoint each, with relatively short session durations (2.22 and 1.50, respectively). However, the lack of classified staypoints with map use likely affected the results. In contrast, user 15 recorded the longest durations in residential areas (3.71), followed closely by food locations (3.48). These findings aligned with the general population, where no significant differences in session duration were noted between food, residential, and transportation areas. Both participants exhibited the lowest values in the transportation category, at -1.11 for user 20 and -1.43 for user 15. This differed from the broader population, where the slowest tap speeds were found in regions associated with tourism and entertainment, at approximately -1.4. The lower tap speed of these categories could hint at the role of increased cognitive load in map use.

The absence of any recorded staypoints classified under tourism, despite visits to foreign countries, suggests that the current method for categorizing 'tourism' staypoints did not effectively capture the app usage patterns of tourists. This approach neglected crucial factors such as an individual's usual place of residence and their frequency of visits to a particular region. For instance, under the existing system, a first-time trip to Greece would not be fully identified as a tourist exploration. Rather, only specific instances, such as visits to historical sites, might be captured, while ignoring periods of low interaction in transit areas where users might engage less frequently with the app due to the unfamiliar environment demanding more of their attention for information processing.

In tripleg contexts, user 15 again had more context-enriched map use than user 20. However, the contextual augmentation of triplegs with motorization speed did not reveal significant differences in session duration or tap speed for either participant. Nevertheless, both participants exhibited longer session durations during slow mobility, a trend consistent with the general population (which was statistically significant). Notably, user 20 had shorter session lengths than user 15, and their slow mobility closely aligned with the fast mobility speeds of user 15. Tap speed also followed a similar pattern, with both participants displaying slower tap speeds during slow mobility. While the general population showed a tap speed of approximately -0.65, the tap speed of user 20 was lower in slow mobility (-0.96) and faster in fast mobility (-0.14). User 15's tap speeds were near the average for slow mobility (-0.64) and only slightly faster in fast mobility (-0.36).

The fact that the general app use behavior of an individual differed from their map app usage underlines the need for specific research into map usage behavior. The findings of the micro-level analysis suggested that individual users had distinct preferences and usage patterns. Thus, map apps could benefit from personalized features that adapt to a user's preferred mode of interaction (e.g., shorter sessions for goal-oriented users, or extended sessions for more exploratory users). This could improve user satisfaction by aligning the app's functionality with user behavior.

5.4 Limitations & Future Research

This study examined the relationship between the use of map applications in the context of human mobility. The tappigraphy method, derived from the field of neuroscience, is distinguished by its high temporal resolution and high validity, making it an effective tool for studying map app usage through the analysis of app session duration and tap speed. The integration of GPS data with tap data enabled the elucidation of the locations and circumstances (stationary vs. non-stationary) of map application usage. However, the approach was subject to several limitations that can affect the generalizability and precision of its findings.

Firstly, the dataset was relatively limited in size, comprising a restricted number of users. Furthermore, map application sessions represent only a minor aspect of overall mobile phone usage, further constraining the available data. As a result, the scope of the conclusions that can be drawn was limited. Moreover, the data may not fully represent the diverse behaviors of users. However, as AAs, the GPS and tappigraphy methods make it possible to scale this to a larger study size and to longer study periods than traditional studies. Although crucial demographic variables such as gender, age, and occupation were not collected due to privacy restrictions, the proposed approach still gives considerable insight into the daily use of mobile map applications.

Another limitation is the exclusion of Apple users, as the study only captured data from Android devices. This introduces a bias in the findings, as it does not account for the behavior of iOS users.

Furthermore, a considerable amount of data was lost during the alignment process, particularly in the case of GPS data, which could potentially introduce biases or inconsistencies in the identification of staypoints and triplegs. A subsequent step would be to examine the impact of re-merging the aligned data aggregated by GPS points with the original GPS dataset on the classifications. This would assist in mitigating the loss of GPS data and ensure that the differentiation between stationary and non-stationary movement is based on a comprehensive understanding of the movement data, regardless of whether taps were recorded or not. Moreover, the precision of GPS-based classification could be improved by incorporating other smartphone collected data. For example, acceleration and gyroscope data could facilitate more precise classifications (Otebolaku and Andrade, 2016; Straczkiewicz et al., 2021; Huang and Onnela, 2020).

The categorization of apps using Google Play Store classifications represented a valuable preliminary step in the selection of map applications. However, these categories are broad, and some apps with similar functions were not consistently classified. For instance, apps related to the purchase of tickets were found in both the “maps and navigation” and the “travel and local” categories, which could complicate the interpretation of map app usage based on the Google Play Store classification. To gain a more precise understanding of map app usage based on the app’s specific purpose, a more detailed classification was necessary. In this study, the refinement of these classifications was conducted manually, which facilitated a more comprehensive understanding of the intended use of the app. However, this procedure was both time-intensive and complex since applications often fulfilled multiple roles, rendering category assignment subjective to the researcher’s discretion. Thus, although the preliminary categorization was beneficial for the initial selection of apps, it is insufficient for more comprehensive analyses.

Moreover, the findings of the study were contingent upon the criteria established for categorizing aligned data into stationary and non-stationary activities. Although uniform thresholds were applied across all subjects to ensure comparability, these thresholds may not fully capture individual variations in movement patterns. For example, for individuals who traveled longer distances, increasing the gap threshold for triplegs could better capture the longer trips, which could provide more accurate classifications. The different thresholds from study to study also makes it more difficult to compare the results with existing literature.

The classification of stationary data by context presented both opportunities and challenges in spatial analysis. While selecting the most frequent tag for a POI was computationally efficient, it may oversimplify the complex nature of space. This method, based on Tobler's first law of geography, assumed spatial auto-correlation (Tobler, 1970). However, it failed to account for the potential overlap of function types within a single location. As Yang et al. (2016, p. 6) noted, the same location may hold various meanings for different individuals at different times, highlighting the semantic complexity of place. The accuracy of such classifications remains uncertain, particularly when applied to clustered staypoints (locations) rather than staypoints.

Finally, in the classification of non-stationary data, motorization speeds were used as a proxy for distinguishing between active and passive modes of transport. To the best of our knowledge, this was the first study to contextualize non-stationary movement. However, this approach was coarse and may have oversimplified the dynamics of user movement. Future research could benefit from more nuanced transport classification methods to capture the full spectrum of mobility behaviors.

Building on the limitations discussed earlier, this thesis opened numerous avenues for further investigation. It uncovered specific user preferences and behaviors in the use of map apps. One practical application of these findings is the design of mobile map apps tailored to individual user profiles to enhance both user satisfaction and spatial learning. At a broader level, the differentiation between stationary and non-stationary use of map apps revealed that users engage with these apps for longer periods while in motion, particularly when moving at slower speeds (< 20 km/h). These findings warrant a further exploration into how mobility impacts map usage, including the potential to enrich touchscreen interactions by adding finer-grained contextual elements related to the user's state of mobility. Such research could inform the development of interfaces optimized for either quick glance interactions or more deliberate use, depending on the state of mobility and context. Since this was the first study to our knowledge to give context to the non-stationary use of maps, future work could refine the geospatial classification to better reflect different modes of transport. Additionally, integrating location-based context with the distance traveled, or examining app usage patterns that occur temporally close to one another or across consecutive app sessions, could provide further valuable insight.

Despite these limitations, it is important to highlight that this study is the first of its kind to employ tappigraphy data—recognized for its high temporal resolution and ecological validity—with GPS data and generate added context to examine map app usage. This innovative approach provides a more nuanced and comprehensive understanding of user behavior by distinguishing between stationary and mobile interactions and contextualizing both states of mobility. The ability to capture these detailed behavioral patterns marks a substantial advancement in the study of human mobility and app usage, offering insights that would not have been possible with traditional methods alone. These contributions underscore the value of current research and demonstrate its capacity to provide valuable insights for further exploration and improvement.

6 Conclusion

This thesis explored the usage patterns of mobile map apps in relation to human mobility and the role of environmental and behavioral contextual enrichment. By leveraging the novel combination of the tappigraphy method and GPS collection, a geospatial analysis of map app usage was performed on a macro- and microscale, revealing significant patterns in touchscreen interactions that aligned with movement types and location-based contextual factors.

Map app usage patterns demonstrated distinct behaviors across both stationary and non-stationary contexts. Irrespective of mobility status, an exponential relationship was observed between the number of taps on map applications and the application name. In terms of map app sessions, users in the non-stationary state engaged longer with map apps than while stationary, whereas stationary users exhibited slightly faster tap rates. This suggests that increased cognitive load may prompt longer map sessions during transit. The analysis also pointed to variations in app usage time depending on the app's intended purpose. Particularly notable was Fairtiq, the check-in check out ticket shop app, which exhibited unique patterns characterized by short sessions and low tap speed. Consistent with (Reichenbacher et al., 2022), a day-night usage pattern was identified with regard to the access of map apps. Moreover, in both stationary and non-stationary contexts, map apps were accessed most often in the mid-afternoon. Additionally, map apps experienced higher usage during weekdays compared to weekends.

The use context of map activity further highlighted variations in touchscreen interactions. For stationary periods, two approaches were utilized to enrich staypoints: the OSNA method to distinguish between home and workplace, and POI categorization using OSM data. The OSNA method did not yield significant differences in map session metrics, such as session duration and tap speed, possibly due to its coarse classification or the impact of remote work. In contrast, the OSM classification demonstrated statistically significant differences in map session duration and tap speed. The results demonstrated that different map applications were utilized depending on the POI context: Google Maps exhibited the highest aggregate tap count in the three most frequent POI categories (residential, transportation, and food-related areas). In contrast to transportation and residential areas, travel booking apps like Tripadvisor and Booking showed higher tap counts than SBB Mobile. Furthermore, vehicle reservation apps registered a higher tap count in food-related places.

To enrich the moving segments, the average speed to a tripleg was computed and classified into slow and fast mobility with a threshold of 20 km/h. In triplegs, proportionally, map apps were accessed twice more often in fast than slow mobility. In addition, map sessions were significantly longer in slow mobility, but no differences were found regarding the tap speed and motorization speed.

At the micro-level, individual user behavior demonstrated that average session length and tap speed in all apps did not directly translate to similar behavior in map apps. Furthermore, longer map app sessions did not imply a lower tap speed. The relatively low number of map sessions for both participants did not reveal significant differences between the different context categories, but showed similar trends to the overall study population.

While these findings offer new insights into mobile map app usage, the study is not without limitations. The alignment of GPS and tappigraphy data resulted in some data loss, which may have impacted the accuracy of contextual classifications. Moreover, the relatively small sample size may limit the generalizability of the results. Future research should focus on expanding the dataset and refining context-enrichment methods.

The practical implications of these findings suggest that map app developers could optimize user experiences by adapting to mobility contexts, such as providing simplified interfaces during fast mobility or more comprehensive interaction options during stationary periods. Additionally, integrating contextual information can enhance user experience by offering personalized, relevant content based on location and state of mobility.

In conclusion, this thesis has demonstrated the value of combining tap with GPS data to examine the everyday use of mobile map apps in real-world contexts. The findings advanced our understanding of how mobility and use context influence app interactions, providing valuable insights for both theoretical research and practical app design. Future studies should continue exploring these dynamics with larger datasets and more granular contextual analyses to deepen our understanding of mobile map usage in everyday life.

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A POI Tags

An overview of the POI tag extracted from OSM is given by the dictionary called tags. To classify these into larger categories, the dictionary tags_classified was used.

```
tags = {
    "amenity": ["restaurant", "pub", "bar", "cafe", "college", "school",
                "university", "bus_station", "charging_station", "casino",
                "cinema", "clinic", "doctors", "hospital"],
    "building": ["apartments", "bungalow", "detached", "house", "residential",
                 "commercial", "retail", "government", "trainstation",
                 "college", "university", "transportation", "hotel"],
    "highway": "bus_stop",
    "public_transport": True,
    "railway": ["station", "tram_stop"],
    "tourism": ["attraction", "hotel", "hostel", "motel", "camp_site",
                "gallery", "museum", "theme_park", "viewpoint", "zoo"]
}

tags_classified = {
    "food": ["restaurant", "pub", "bar", "cafe", "fast_food"],
    "education": ["college", "school", "university"],
    "transportation": ["bus_station", "fuel", "parking", "charging_station",
                       "trainstation", "station", "tram_stop", "stop_position",
                       "platform", "stop_area", "stop_area_group",
                       "ferry_terminal", "transportation", "bus_stop",
                       "technical_station", "platform_section", "footway"],
    "entertainment": ["casino", "cinema", "arts_centre", "gallery", "museum",
                      "theme_park", "zoo", "viewpoint"],
    "healthcare": ["clinic", "doctors", "hospital"],
    "residential": ["apartments", "bungalow", "detached", "house", "residential"],
    "commercial": ["commercial", "retail", "government", "townhall"],
    "tourism": ["attraction", "hotel", "hostel", "motel", "castle", "camp_site"]
}
```

B Map App Usage Metrics

Table 7: Cumulative Tap Count by Map App

App Name	sp_map_tap_count	tpls_map_tap_count	total_map_tap_count
com.google.android.apps.maps	22'797	94'275	117'072
ch.sbb.mobile.android.b2c	12'251	32'194	44'445
com.booking	1'686	11'226	12'912
net.osmand.plus	2'788	6'952	9'740
com.mobilityado.ado	150	7'237	7'387
ch.publibike.app	3'996	3'337	7'333
ch.admin.swisstopo	1'222	5'779	7'001
com.tripadvisor.tripadvisor	2'003	3'855	5'858
com.mapswithme.maps.pro	1'001	3'655	4'656
com.flightradar24free	198	3'092	3'290
com.airbnb.android	413	2'480	2'893
com.lynxspa.prontotreno	626	1'620	2'246
pt.carris.tecmic	1'632	210	1'842
ch.futurecom.zoozurich	0	1'668	1'668
de.actionbound	1'081	419	1'500
com.yoc.swiss.swiss	206	1'044	1'250
com.fairtiq.android	321	785	1'106
com.lufthansa.android.lufthansa	138	843	981
com.app.stadtblatt	303	580	883
ch.schweizmobil	17	758	775
org.paoloconte.treni_lite	221	487	708
com.comuto	102	548	650
it.nordcom.app	125	525	650
org.eurail.railplanner	58	528	586
com.ubercab	105	480	585
com.google.earth	0	518	518
com.airfrance.android.dinamoprd	248	159	407
com.bonfire.matterhorn	166	233	399
com.ebookers	0	385	385
com.live.flighttracker	0	385	385
com.vsct.vsc.mobile.horaireetresa.android	18	364	382
ch.local.android	32	340	372
org.bikecityguide	13	333	346
com.hostelworld.app	0	345	345
net.skyscanner.android.main	0	316	316
com.limebike	191	95	286
ch.mobility.mobidroid.main	23	258	281
de.hafas.android.zvv	30	236	266
com.blablalines	0	241	241
co.bird.android	208	23	231
com.plannet.milesandmoreapp	9	218	227
com.staralliance.navigator	0	208	208
de.flixbus.app	8	188	196
com.iberia.android	4	189	193
ch.mnc.zvv.oneapp	40	141	181
com.thetrainline	48	131	179
ch.search.android.search	52	101	153
com.riliclabs.countriesbeen	0	149	149
de.swm.mvgfahrinfo.muenchen	54	85	139
net.osmand	0	136	136
net.pluservice.ticketbv	15	115	130
de.hafas.android.db	17	106	123
it.sistema3.apps.ibeach	5	115	120
ch.carvelo2go.app	0	102	102
ch.parkingcard.customer	0	74	74
com.peaklens.ar	47	24	71
ch.sbb.prail2	0	36	36
ch.stadt.winterthur.moapp	0	36	36
com.wemlin.android	0	29	29
de.eos.uptrade.android.fahrinfo.berlin	0	28	28
org.peakfinder.area.alps	0	27	27
com.here.app.maps	0	23	23
mnc.android.zvvticket	0	23	23
de.infas.mobico	0	21	21
ch.sbb.myway	0	14	14
com.aegean.android	0	6	6
com.relayrides.android.relayrides	0	2	2
com.attidomobile.passwallet	2	0	2

	TRAVEL_AND_LOCAL
	MAPS_AND_NAVIGATION

Table 8: Map App Session Metrics by State of Mobility and App Category

App Name	App Name Abbreviation	App Use	Median of Log Median SP Session Duration [s]	Median of Log Median SP Tap Speed [taps/s]	SP Count with Map App Use	Median of Log Median TPLS Session Duration [s]	Median of Log Median TPLS Tap Speed [taps/s]	TPLS Count with Map App Use
ch.admin.swisstopo	swisstopo	Navigation	3.58	-0.81	41	4.34	-0.84	107
ch.carvelo2go.app	carvelo	Reserve automobile, bike, scooter				4.10	-0.46	2
ch.futurecom.zoozurich	Zoo Zürich	Navigation				5.20	-0.67	5
ch.local.android	local.ch	Sightseeing	3.90	-0.43	1	3.04	-0.52	18
ch.mnc.zvv.oneapp	ZVV	Ticket shop public transport (train, bus)	4.23	-0.54	1	3.60	-0.60	2
ch.mobility.mobidroid.main	Mobility Swiss	Reserve automobile, bike, scooter	2.51	-0.46	1	2.80	-0.85	12
ch.parkingcard.customer	Parkingpay	Other				6.67	-2.37	1
ch.publibike.app	Publibike	Reserve automobile, bike, scooter	2.47	-0.58	299	2.62	-0.79	230
ch.sbb.mobile.android.b2c	SBB Mobile	Ticket shop public transport (train, bus)	2.89	-0.81	945	3.24	-0.79	1506
ch.sbb.myway	MyWay	Tracking				3.72	-1.09	1
ch.sbb.prail2	P+Rail	Other				2.25	-0.91	1
ch.schweizmobil	SchweizMobil	Navigation	1.79	0.08	2	5.47	-0.83	4
ch.search.android.search	search.ch	Navigation	2.13	-0.10	2	3.65	-0.29	1
ch.stadt.winterthur.moapp	Winterthur	Information				4.42	-0.83	1
co.bird.android	Bird	Reserve automobile, bike, scooter	3.03	-1.10	2	4.23	-1.09	1
com.aegean.android	Aegean Airlines	Flight / Airlines				2.49	-0.70	1
com.airbnb.android	Airbnb	Book travel plans (hotel, flight, car)	3.88	-0.55	5	4.16	-0.54	12
com.airfrance.android.dinamoprd	AirFrance	Flight / Airlines	5.21	-1.38	4	4.02	-1.01	10
com.app.stadtblatt	Stadblatt	Information	4.30	-0.69	5	4.37	-1.55	26
com.attidomobile.passwallet	PassWallet	Sightseeing	1.30	-0.61	1			
com.blablalines	BlaBlaCar Daily	Reserve automobile, bike, scooter				5.43	-0.71	1
com.bonfire.matterhorn	Matterhorn	Ticket shop public transport (train, bus)	5.55	-0.44	1	1.71	-0.10	1
com.booking	Booking.com	Book travel plans (hotel, flight, car)	2.79	-0.30	7	4.23	-0.77	37
com.comuto	BlaBlaCar	Reserve automobile, bike, scooter	5.04	-1.48	1	4.30	-0.90	4
com.ebookers	ebookers	Book travel plans (hotel, flight, car)				2.45	0.01	4
com.fairtiq.android	Fairtiq	Ticket shop public transport (train, bus)	0.86	0.14	52	1.29	-0.24	130
com.flightradar24free	Flightradar24Free	Flight / Airlines	4.25	-1.49	6	3.25	-0.75	75
com.google.android.apps.maps	Google Maps	Navigation	3.18	-0.35	676	3.73	-0.38	1598
com.google.earth	Google Earth	Information				5.71	-1.10	2
com.here.app.maps	HERE WeGo	Offline Navigation				1.66	-0.28	1
com.hostelworld.app	Hostelworld	Book travel plans (hotel, flight, car)				3.28	-0.59	4
com.iberia.android	Iberia	Flight / Airlines	2.56	-1.17	1	4.19	-1.10	3
com.limebike	Lime	Reserve automobile, bike, scooter	1.10	-0.41	1	5.07	-2.03	1
com.live.flighttracker	Live Flight Tracker	Flight / Airlines				4.52	-0.53	1
com.lufthansa.android.lufthansa	Lufthansa	Flight / Airlines	2.93	-0.67	4	3.68	-0.79	10
com.lynxspa.prontotreno	Trenitalia	Ticket shop public transport (train, bus)	2.41	-0.76	33	2.71	-0.95	55
com.mapswithme.maps.pro	MAPS.ME: Offline maps GPS Nav	Offline Navigation	3.46	-0.46	23	3.88	-0.50	59
com.mobilityado.ado	ADO Boletos de Autobús	Ticket shop public transport (train, bus)	4.48	-1.05	1	4.34	-1.22	17
com.peaklens.ar	PeakLens	Sightseeing	3.20	-1.12	1	2.64	-0.35	3
com.plannet.milesandmoreapp	Miles & More	Flight / Airlines	0.23	0.46	1	0.52	0.40	2
com.relayrides.android.relayrides	Turo	Reserve automobile, bike, scooter				-0.68	1.37	1
com.riliclabs.countriesbeen	Countries Been	Other				4.89	0.12	1
com.staralliance.navigator	Star Alliance	Flight / Airlines				0.22	0.47	4
com.thetrainline	Trainline	Ticket shop public transport (train, bus)	0.94	0.37	4	2.40	-0.35	8
com.tripadvisor.tripadvisor	Tripadvisor	Book travel plans (hotel, flight, car)	4.05	-0.17	5	3.30	-0.20	9
com.ubercab	Uber	Reserve automobile, bike, scooter	4.22	-0.95	2	3.59	-0.70	9
com.vsct.vsc.mobile.horaireetresa.android	SNCF Connect	Ticket shop public transport (train, bus)	2.43	-0.42	1	2.68	-0.98	5
com.wemlin.android	Wemlin	Information				1.97	0.37	3
com.yoc.swiss.swiss	SWISS	Flight / Airlines	2.42	-0.31	8	2.90	-0.77	16
de.actionbound	Actionbound	Entertainment	2.98	-0.41	14	3.02	-0.65	8
de.eos.uptrade.android.fahrinfo.berlin	BVG Fahrinfo	Ticket shop public transport (train, bus)				4.17	-1.53	2
de.flixbus.app	Flixbus	Ticket shop public transport (train, bus)	2.08	0.00	1	4.52	-0.84	5
de.hafas.android.db	DB Navigator	Ticket shop public transport (train, bus)	2.33	-1.63	3	3.24	-0.85	7
de.hafas.android.zvv	ZVV-Timetable	Information	2.24	-0.57	4	2.80	-0.77	11
de.infas.mobico	infas mobico	Tracking				3.03	-0.84	2
de.swm.mvgfahrinfo.muenchen	MVG Fahrinfo München	Ticket shop public transport (train, bus)	3.20	-1.30	3	3.06	-0.59	6
it.nordcom.app	Trenord	Ticket shop public transport (train, bus)	1.34	-0.10	4	3.30	-0.62	8
it.sistema3.apps.ibeach	iBeach.it	Book travel plans (hotel, flight, car)	2.28	-0.67	1	2.00	-0.21	1
mnc.android.zvvticket	ZVV-Tickets	Ticket shop public transport (train, bus)				2.43	-0.49	1
net.osmand	OsmAnd	Offline Navigation				5.82	-0.91	1
net.osmand.plus	OsmAnd+	Offline Navigation	4.15	-1.42	103	4.51	-1.23	175
net.pluservice.ticketbv	Ticket bus Verona	Ticket shop public transport (train, bus)	2.39	-0.60	1	3.94	-0.46	3
net.skyscanner.android.main	Skyscanner	Book travel plans (hotel, flight, car)				4.11	-1.05	4
org.bikecityguide	Bike Citizens	Navigation	2.90	-0.33	1	3.65	-0.55	10
org.eurail.railplanner	Eurail/Interrail Rail Planer	Information	2.92	-0.63	2	3.44	-0.44	12
org.paoloconte.treni_lite	Orario Treni	Ticket shop public transport (train, bus)	3.29	-0.92	8	3.67	-0.71	17
org.peakfinder.area.alps	PeakFinder	Sightseeing				3.38	-0.16	1
pt.carris.tecmic	Carris	Ticket shop public transport (train, bus)	3.92	-0.64	7	2.52	0.08	3
Median			3.03	-0.55	4	3.70	-0.70	4
Durchschnitt			2.96	-0.62	50.87	3.45	-0.64	63.91

App Category
TRAVEL_AND_LOCAL
MAPS_AND_NAVIGATION

C Dunn's Test Outputs

C.1 Staypoint Map Session Metrics

Table 9: Dunn's Test Results for the Log Duration of Staypoint App Sessions by Map App (a=0.01)

App Name	ch.admin.swisstopo	ch.local.android	ch.mnc.zvv.oneapp	ch.mobility.mobidroid.main	ch.publibike.app	ch.sbb.mobile.android.b2c	ch.schweizmobil	ch.search.android.search	co.bird.android	com.airbnb.android	com.airfrance.android.dinamoprd	com.app.stadtblatt	com.attidomobile.passwallet	com.bonfire.matterhorn	com.booking	com.comuto	com.fairtiq.android	com.flightradar24free	com.google.android.apps.maps	com.iberia.android	com.limebike	com.lufthansa.android.lufthansa	com.lynxspa.prontotreno	com.mapswithme.maps.pro	com.mobilityado.ado	com.peaklens.ar	com.plannet.milesandmoreapp	com.thetrainline	com.tripadvisor.tripadvisor	com.ubercab	com.vsct.vsc.mobile.horaireetresa.android	com.yoc.swiss.swiss	de.actionbound	de.flixbus.app	de.hafas.android.db	de.hafas.android.zvv	de.swm.mvgfahrinfo.muenchen	it.nordcom.app	it.sistema3.apps.ibeach	net.osmand.plus	net.pluservice.ticketbv	org.bikecityguide	org.eurail.railplanner	org.paoloconte.treni_lite	pt.carris.tecmic
ch.admin.swisstopo	1	1	1	1	0.0058	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.local.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.mnc.zvv.oneapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.mobility.mobidroid.main	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.publibike.app	0.0058	1	1	1	1	0.0015	1	1	1	1	1	1	1	1	1	1	0.0000	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1
ch.sbb.mobile.android.b2c	1	1	1	1	0.0015	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1
ch.schweizmobil	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.search.android.search	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
co.bird.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airbnb.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0204	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airfrance.android.dinamoprd	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0112	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.app.stadtblatt	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.2905	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.attidomobile.passwallet	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.bonfire.matterhorn	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.booking	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.comuto	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.fairtiq.android	0.0000	1	1	1	0.0000	0.0000	1	1	1	0.0204	0.0112	0.2905	1	1	1	1	1	0.0004	0.0000	1	1	1	0.0571	0.0000	1	1	1	1	0.0109	1	1	1	0.0135	1	1	1	1	1	1	0.0000	1	1	1	0.1547	0.0114
com.flightradar24free	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0004	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.google.android.apps.maps	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1
com.iberia.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.limebike	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lufthansa.android.lufthansa	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lynxspa.prontotreno	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0571	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0006	1	1	1	1	1
com.mapswithme.maps.pro	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.mobilityado.ado	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.peaklens.ar	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.plannet.milesandmoreapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.thetrainline	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.tripadvisor.tripadvisor	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0109	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.ubercab	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.vsct.vsc.mobile.horaireetresa.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.yoc.swiss.swiss	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.actionbound	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0135	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.flixbus.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.db	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.zvv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.swm.mvgfahrinfo.muenchen	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.nordcom.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.sistema3.apps.ibeach	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.osmand.plus	1	1	1	1	0.0000	0.0000	1	1	1	1	1	1	1	1	1	1	0.0000	1	0.0000	1	1	1	0.0006	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.pluservice.ticketbv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.bikecityguide	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.eurail.railplanner	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.paoloconte.treni_lite	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.1547	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
pt.carris.tecmic	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0114	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 10: Dunn's Test Results for the Log Tap Speed in Staypoint App Sessions by Map App (a=0.01)

App Name	ch.admin.swisstopo	ch.local.android	ch.mnc.zvv.oneapp	ch.mobility.mobidroid.main	ch.publibike.app	ch.sbb.mobile.android.b2c	ch.schweizmobil	ch.search.android.search	co.bird.android	com.airbnb.android	com.airfrance.android.dinamoprd	com.app.stadtblatt	com.attidomobile.passwallet	com.bonfire.matterhorn	com.booking	com.comuto	com.fairtiq.android	com.flightradar24free	com.google.android.apps.maps	com.iberia.android	com.limebike	com.lufthansa.android.lufthansa	com.lynxspa.prontotreno	com.mapswithme.maps.pro	com.mobilityado.ado	com.peaklens.ar	com.plannet.milesandmoreapp	com.thetrainline	com.tripadvisor.tripadvisor	com.ubercab	com.vsct.vsc.mobile.horaireetresa.android	com.yoc.swiss.swiss	de.actionbound	de.flixbus.app	de.hafas.android.db	de.hafas.android.zvv	de.swm.mvgfahrinfo.muenchen	it.nordcom.app	it.sistema3.apps.ibeach	net.osmand.plus	net.pluservice.ticketbv	org.bikecityguide	org.eurail.railplanner	org.paoloconte.treni_lite	pt.carris.tecmic
ch.admin.swisstopo	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0004	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.local.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.mnc.zvv.oneapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.mobility.mobidroid.main	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.publibike.app	1	1	1	1	1	0.0074	1	1	1	1	1	1	1	1	1	1	0.0005	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1
ch.sbb.mobile.android.b2c	1	1	1	1	0.0074	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0052	1	1	1	1	1
ch.schweizmobil	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.search.android.search	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
co.bird.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airbnb.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airfrance.android.dinamoprd	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.app.stadtblatt	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.attidomobile.passwallet	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.bonfire.matterhorn	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.booking	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.comuto	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.fairtiq.android	0.0004	1	1	1	0.0005	0.0000	1	1	1	1	1	1	1	1	1	1	1	0.7353	0.0707	1	1	1	0.3311	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1
com.flightradar24free	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.7353	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.google.android.apps.maps	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	0.0707	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1
com.iberia.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.limebike	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lufthansa.android.lufthansa	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lynxspa.prontotreno	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3311	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.2719	1	1	1	1	1
com.mapswithme.maps.pro	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.2379	1	1	1	1	1
com.mobilityado.ado	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.peaklens.ar	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.plannet.milesandmoreapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.thetrainline	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.tripadvisor.tripadvisor	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.ubercab	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.vsct.vsc.mobile.horaireetresa.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.yoc.swiss.swiss	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.actionbound	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3672	1	1	1	1	1
de.flixbus.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.db	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.zvv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.swm.mvgfahrinfo.muenchen	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.nordcom.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.sistema3.apps.ibeach	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.osmand.plus	1	1	1	1	0.0000	0.0052	1	1	1	1	1	1	1	1	1	1	0.0000	1	0.0000	1	1	1	0.2719	0.2379	1	1	1	1	1	1	1	1	0.3672	1	1	1	1	1	1	1	1	1	1	1	1
net.pluservice.ticketbv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.bikecityguide	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.eurail.railplanner	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.paoloconte.treni_lite	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
pt.carris.tecmic	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

C.2 Tripleg Map Session Metrics

Table 11: Dunn's Test Results for the Log Duration of Tripleg App Sessions by Map App (a=0.01)

App Name	ch.admin.swisstopo	ch.carvelo2go.app	ch.futurecom.zoozurich	ch.local.android	ch.mnc.zvv.oneapp	ch.mobility.mobidroid.main	ch.parkingcard.customer	ch.publibike.app	ch.sbb.mobile.android.b2c	ch.sbb.myway	ch.sbb.prail2	ch.schweizmobil	ch.search.android.search	ch.stadt.winterthur.moapp	co.bird.android	com.aegean.android	com.airbnb.android	com.airfrance.android.dinamoprd	com.app.stadtblatt	com.blablalines	com.bonfire.matterhorn	com.booking	com.comuto	com.ebookers	com.fairtiq.android	com.flightradar24free	com.google.android.apps.maps	com.google.earth	com.here.app.maps	com.hostelworld.app	com.iberia.android	com.limebike	com.live.flighttracker	com.lufthansa.android.lufthansa	com.lynxspa.prontotreno	com.mapswithme.maps.pro	com.mobilityado.ado	com.peaklens.ar	com.plannet.milesandmoreapp	com.relayrides.android.relayrides	com.rilicilabs.countriesbeen	com.staralliance.navigator	com.thetrainline	com.tripadvisor.tripadvisor	com.ubercab	com.vsct.vsc.mobile.horaireetresa.android	com.wemlin.android	com.yoc.swiss.swiss	de.actionbound	de.eos.uptrade.android.fahrinfo.berlin	de.flixbus.app	de.hafas.android.db	de.hafas.android.zvv	de.infas.mobico	de.swm.mvgfahrinfo.muenchen	it.nordcom.app	it.sistema3.apps.ibeach	mnc.android.zvvticket	net.osmand	net.osmand.plus	net.pluservice.ticketbv	net.skyscanner.android.main	org.bikecityguide	org.eurail.railplanner	org.paoloconte.treni_lite	org.peakfinder.area.alps	pt.carris.tecmic
ch.admin.swisstopo	1	1	1	0.4500	1	1	1	0.0000	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	0.2274	1	1	1	1	1	1	1	1	0.0014	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.carvelo2go.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.futurecom.zoozurich	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0328	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.local.android	0.4500	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.7609	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.1164	1	1	1	1	1	1	1
ch.mnc.zvv.oneapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.mobility.mobidroid.main	1	1	1	1	1	1	1	1	<<<<<<<<	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3882	1	1	1	1	1	1	1
ch.parkingcard.customer	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.publibike.app	0.0000	1	1	1	1	1	1	1	0.2771	1	1	0.9046	1	1	1	1	1	1	0.0541	1	1	0.0000	1	1	0.0000	1	0.0000	1	1	1	1	1	1	1	1	0.0611	0.0229	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1
ch.sbb.mobile.android.b2c	0.0000	1	1	1	1	1	1	0.2771	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0100	1	1	0.0000	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1
ch.sbb.myway	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.sbb.prail2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.schweizmobil	1	1	1	1	1	1	1	0.9046	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0017	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.search.android.search	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.stadt.winterthur.moapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
co.bird.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.aegean.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airbnb.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0004	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airfrance.android.dinamoprd	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0898	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.app.stadtblatt	1	1	1	1	1	1	1	0.0541	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.blablalines	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.bonfire.matterhorn	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.booking	1	1	1	0.7609	1	1	1	0.0000	0.0100	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	0.0434	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.comuto	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.4918	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.ebookers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.fairtiq.android	0.0000	1	0.0328	1	1	1	1	0.0000	0.0000	1	1	0.0017	1	1	1	1	0.0004	0.0898	0.0000	1	1	0.0000	0.4918	1	1	0.0000	0.0000	0.5587	1	1	1	1	1	1	0.0002	0.0000	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	0.2407	0.0522	0.0030	1	1
com.flightradar24free	0.2274	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0080	1	1	1	1	1	1	1
com.google.android.apps.maps	1	1	1	1	1	1	1	0.0000	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	0.9324	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0014	1	1	1	1	1	1	1
com.google.earth	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5587	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.here.app.maps	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.hostelworld.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.iberia.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.limebike	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.live.flighttracker	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lufthansa.android.lufthansa	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lynxspa.prontotreno	0.0014	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0434	1	1	0.0002	1	0.9324	1	1	1	1	1	1	1	1	1	0.8965	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1
com.mapswithme.maps.pro	1	1	1	1	1	1	1	0.0611	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.mobilityado.ado	1	1	1	1	1	1	1	0.0229	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	0.8965	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.peaklens.ar	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.plannet.milesandmoreapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.relayrides.android.relayrides	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.riliclabs.countriesbeen	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.staralliance.navigator	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.thetrainline	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.tripadvisor.tripadvisor	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.ubercab	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.vsct.vsc.mobile.horaireetresa.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.wemlin.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.yoc.swiss.swiss	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.actionbound	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.eos.uptrade.android.fahrinfo.berlin	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.flixbus.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.db	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.zvv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.infas.mobico	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.swm.mvgfahrinfo.muenchen	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.nordcom.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.sistema3.apps.ibeach	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
mnc.android.zvvticket	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.osmand	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.osmand.plus	1	1	1	0.1164	1	0.3882	1	0.0000	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	0.0080	0.0014	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.pluservice.ticketbv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.skyscanner.android.main	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.bikecityguide	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.2407	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.eurail.railplanner	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0522	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.paoloconte.treni_lite	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0030	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.peakfinder.area.alps	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
pt.carris.tecmic	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 12: Dunn's Test Results for the Log Tap Speed in Tripleg App Sessions by Map App (a=0.01)

App Name	ch.admin.swisstopo	ch.carvelo2go.app	ch.futurecom.zoozurich	ch.local.android	ch.mnc.zvv.oneapp	ch.mobility.mobidroid.main	ch.parkingcard.customer	ch.publibike.app	ch.sbb.mobile.android.b2c	ch.sbb.myway	ch.sbb.prail2	ch.schweizmobil	ch.search.android.search	ch.stadt.winterthur.moapp	co.bird.android	com.aegean.android	com.airbnb.android	com.airfrance.android.dinamoprd	com.app.stadtblatt	com.blablalines	com.bonfire.matterhorn	com.booking	com.comuto	com.ebookers	com.fairtiq.android	com.flightradar24free	com.google.android.apps.maps	com.google.earth	com.here.app.maps	com.hostelworld.app	com.iberia.android	com.limebike	com.live.flighttracker	com.lufthansa.android.lufthansa	com.lynxspa.prontotreno	com.mapswithme.maps.pro	com.mobilityado.ado	com.peaklens.ar	com.plannet.milesandmoreapp	com.relayrides.android.relayrides	com.riliclabs.countriesbeen	com.staralliance.navigator	com.thetrainline	com.tripadvisor.tripadvisor	com.ubercab	com.vsct.vsc.mobile.horaireetresa.android	com.wemlin.android	com.yoc.swiss.swiss	de.actionbound	de.eos.uptrade.android.fahrinfo.berlin	de.flixbus.app	de.hafas.android.db	de.hafas.android.zvv	de.infas.mobico	de.swm.mvgfahrinfo.muenchen	it.nordcom.app	it.sistema3.apps.ibeach	mnc.android.zvvticket	net.osmand	net.osmand.plus	net.pluservice.ticketbv	net.skyscanner.android.main	org.bikecityguide	org.eurail.railplanner	org.paoloconte.treni_lite	org.peakfinder.area.alps	pt.carris.tecmic
ch.admin.swisstopo	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.carvelo2go.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.futurecom.zoozurich	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.local.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.9203	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.9832	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0985	1	1	1	1	1	1	1
ch.mnc.zvv.oneapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.mobility.mobidroid.main	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.parkingcard.customer	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.publibike.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0093	1	0.0041	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0002	1	1	1	1	1	1	1
ch.sbb.mobile.android.b2c	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	0.0000	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0001	1	1	1	1	1	1	1
ch.sbb.myway	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.sbb.prail2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.schweizmobil	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.search.android.search	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ch.stadt.winterthur.moapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
co.bird.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.aegean.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airbnb.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.airfrance.android.dinamoprd	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.app.stadtblatt	1	1	1	0.9203	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0005	1	0.0042	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.4102	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.blablalines	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.bonfire.matterhorn	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.booking	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.comuto	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.ebookers	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.fairtiq.android	0.0000	1	1	1	1	1	1	0.0093	0.0000	1	1	1	1	1	1	1	1	1	0.0005	1	1	1	1	1	1	0.2026	1	1	1	1	1	1	1	1	0.1905	1	0.0053	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1
com.flightradar24free	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.2026	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.google.android.apps.maps	0.0000	1	1	1	1	1	1	0.0041	0.0000	1	1	1	1	1	1	1	1	1	0.0042	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0383	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	1	1	1	1	1	1
com.google.earth	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.here.app.maps	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.hostelworld.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.iberia.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.limebike	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.live.flighttracker	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lufthansa.android.lufthansa	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.lynxspa.prontotreno	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.1905	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.mapswithme.maps.pro	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0224	1	1	1	1	1	1	1
com.mobilityado.ado	1	1	1	0.9832	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0053	1	0.0383	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3714	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.peaklens.ar	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.plannet.milesandmoreapp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.relayrides.android.relayrides	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.riliclabs.countriesbeen	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.staralliance.navigator	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.thetrainline	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.tripadvisor.tripadvisor	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.4102	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.3714	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.1288	1	1	1	1	1	1	1
com.ubercab	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.vsct.vsc.mobile.horaireetresa.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.wemlin.android	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
com.yoc.swiss.swiss	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.actionbound	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.eos.uptrade.android.fahrinfo.berlin	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.flixbus.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.db	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.hafas.android.zvv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.infas.mobico	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
de.swm.mvgfahrinfo.muenchen	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.nordcom.app	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
it.sistema3.apps.ibeach	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
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net.osmand	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.osmand.plus	1	1	1	0.0985	1	1	1	0.0002	0.0001	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.0000	1	0.0000	1	1	1	1	1	1	1	1	0.0224	1	1	1	1	1	1	1	0.1288	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.pluservice.ticketbv	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
net.skyscanner.android.main	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.bikecityguide	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.eurail.railplanner	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.paoloconte.treni_lite	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
org.peakfinder.area.alps	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
pt.carris.tecmic	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Personal Declaration

I hereby declare that the submitted Thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the Thesis. Furthermore, AI applications such as ChatGPT4 and DeepL Write were used to improve the readability and quality of the text.

A. Signer

Aiyana Signer Del Cid, 30.09.2024